

HOW TO MODEL AND SOLVE ENERGY OPTIMIZATION PROBLEMS

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Acknowledgments

- Susara van den Heever, IBM
- Jeremy Bloom, IBM
- Charles (Chip) Wilkins, IBM
- Robert Ashford (Optimization Direct, Inc.)

Agenda

- Intro Optimization Direct
- CPLEX Optimization Studio
- Energy Applications
- Unit Commitment
- Uncertainty toolbox IBM

Optimization Direct

- IBM Business Partner
- More than 30 years of experience in developing and selling Optimization software
- Experience in implementing optimization technology in all the verticals
- Sold to end users – Fortune 500 companies
- Train our customers to get the maximum out of the IBM software
- Help the customers get a kick start and get the maximum from the software right from the start

Which software?

- CPLEX Optimization Studio
- CPLEX is the leader in optimization technology
- CPLEX can handle large scale problems and solve them very fast

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Why IBM? Why CPLEX?

- Fast
- Reliable
- IBM software
- Large scale
- Gives you the ability to model develop and solve your decision problem
- Complete solution

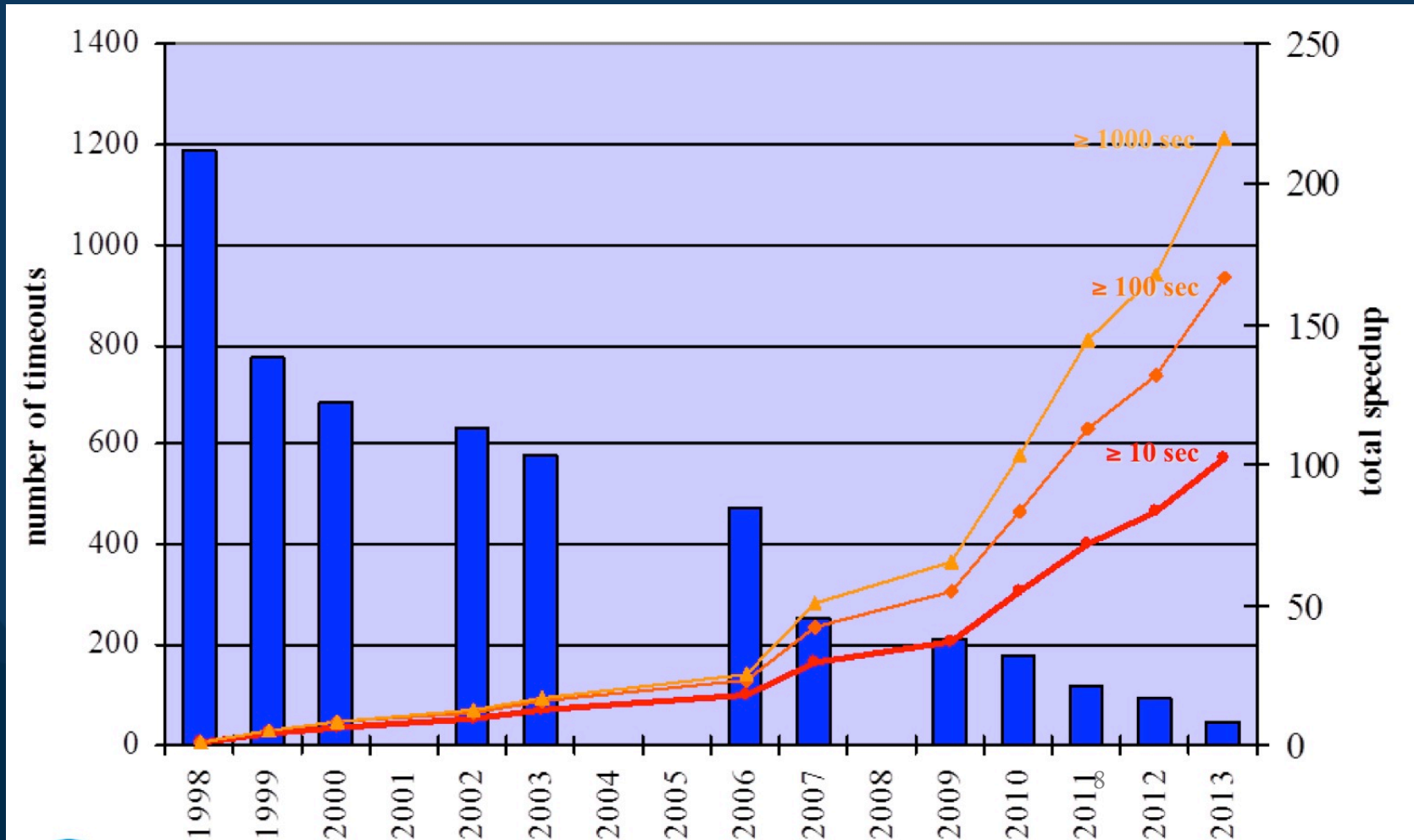
6

How can we help?

- Benchmark your problems?
- Help you with next steps for developing your solution!
- Develop optimization prototypes using OPL

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CPLEX Performance



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Energy Problems

- Network Planning
- Product Portfolio Planning
- Capital Investment
- Resource Planning
- Unit Commitment/Economic Dispatch
- Optimal Power flow / Security Constrained Dispatch

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Unit Commitment Paradigm

- June 1989, Electrical Power Energy, EPRI GS-6401:
 - “Mixed Integer Programming is a powerful Modeling tool, They are , However, theoretical complicated and computationally cumbersome”
- California 7-day model:
- Reported results 1989 – machine unknown
 - 2 day model: 8 hours, no progress
 - 7 day model: 1 hour only to solve the LP

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CPLEX MIP Performance and the Unit Commitment Paradigm

- California 7-day model
 - 1999 results on a desktop PC
 - CPLEX 6.5: 22 minutes, Optimal
 - 2007 results on a desktop PC
 - CPLEX 11.0: 71 seconds, optimal
- What has happened?
 - CPLEX MIP has become the standard approach for UC applications
 - CPLEX MIP early adopters

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CPLEX MIP Performance and the Unit Commitment Paradigm

- What has happened?
 - CPLEX MIP has become the standard approach for UC applications
 - CPLEX MIP early adopters gained a competitive advantage
 - Applications have expanded and changed
 - 1000-2000 generation units simultaneously (Day Ahead Market)
 - Solution Cycles less than 5 minutes (Real Time Market)
 - Uncertainty – We start solving problems with
 - Scenario Generation
 - Stochastic
 - Robust

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Why we can succeed with CPLEX MIP?

- Computers are faster
- Good model formulations – “good modeling”
- Cutting Planes: Valid, redundant inequalities that tighten the linear relaxation
- Heuristics: inexpensive methods for converting a relaxation solution into an integer feasible solution

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Computers are faster

- Parallel cores on commodity chips have become standard in recent years
- CPLEX has the best
 - Parallel implementation for Barrier
 - Parallel NonDeterministic MIP
 - Parallel Deterministic MIP (Make the regulators Happy)
- Parallelism is enabled by default

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CPLEX – Cuts – Valid Inequalities

- Reduce size of LP feasible region
- Cut out parts where there are no integer solutions
- (Usually) reduce number of integer infeasibilities
 - Improves branching
 - Improves performance of heuristics
- Mostly added during root solve, some added in tree
- Dramatic benefit in overall performance

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CPLEX – Cuts – Valid Inequalities

- 1335 models in IBM test set which take ≥ 10 secs and $\leq 10,000$ secs
(Cplex 12.5, Xeon E5430 12 cores 2.66GHZ)
- Fail to solve 28% at all without cuts
- Those that do solve take 6 X longer

Achterberg and Wonderling, 2013

CPLEX - Heuristics

- Attempt to find integer feasible solutions
- (Relatively) quick
- Work either by inspection or by solving a (possibly sequence of) small sub-models
- Can reduce solution times by reduced-cost fixing, root termination during cutting and pruning search tree
- On those 1335 test models
 - 11% fail to solve without heuristics
 - Those that do take 2 X longer

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CPLEX- Heuristics

- Useful in their own right if don't require proof of optimality
- Essential for many large models where never get a solution from branching
- Cplex heuristics include
 - local branching
 - RINS
 - feasibility pump
 - (genetic) solution polishing

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CPLEX – Model Structure

- CPLEX Optimization Studio
- Write models quickly
- Test
- Debug
- And start deploying

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Unit Commitment and the future

- GOAL 1: FERC Meeting (June 2014): most of the new problems involve
 - Stochastic
 - Robust
 - Scenario Based
 - Monte Carlo Simulation and run many problems
- Goal 2: Solve many problems faster
 - Take advantage of the architecture
 - Do better and faster modeling

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IBM – Toolbox for Uncertainty Optimization

- Joint Program between IBM Research and Decision Optimization
- If you want more info please contact Optimization Direct and we can organize a more detailed Webinar

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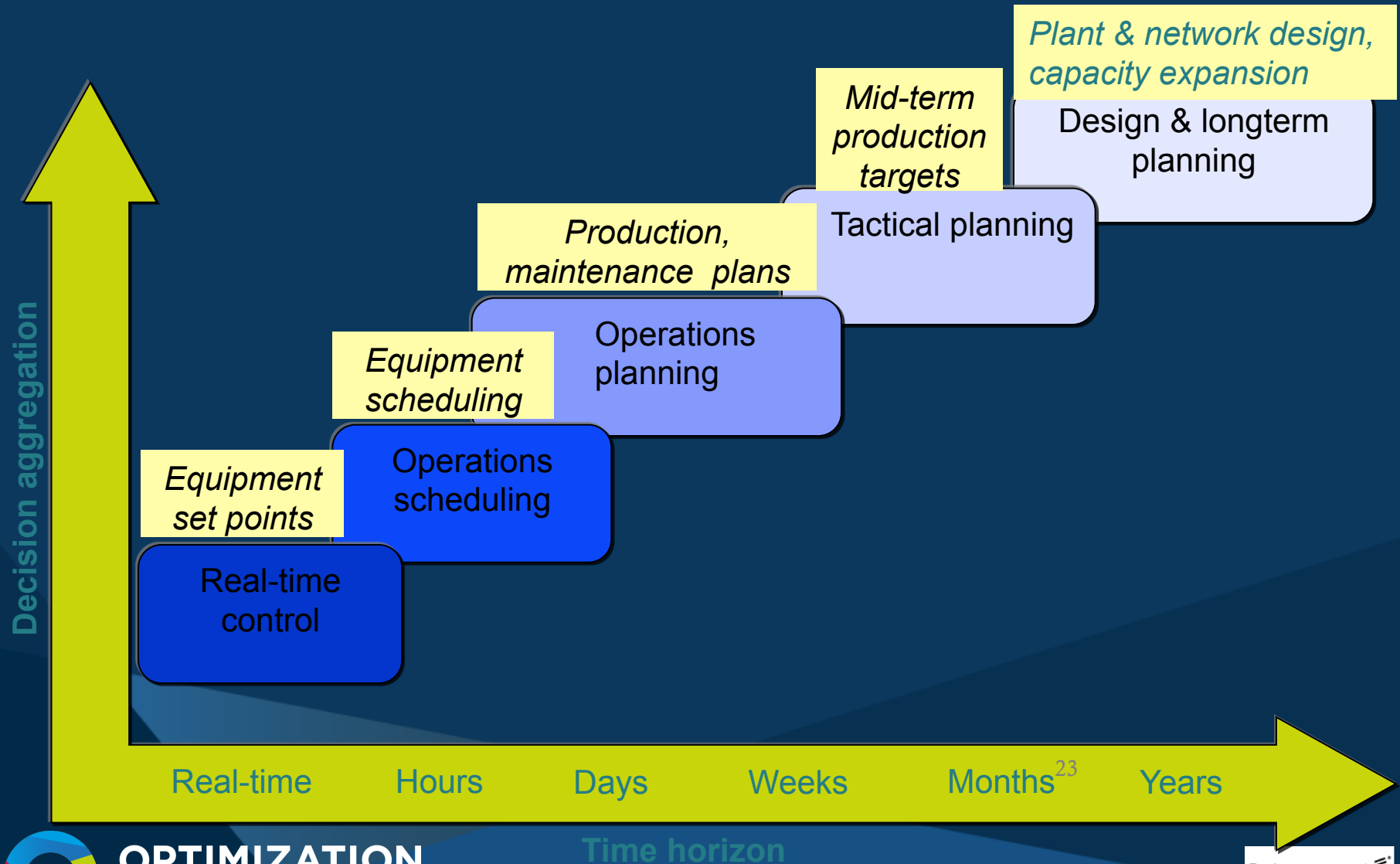
Planning levels



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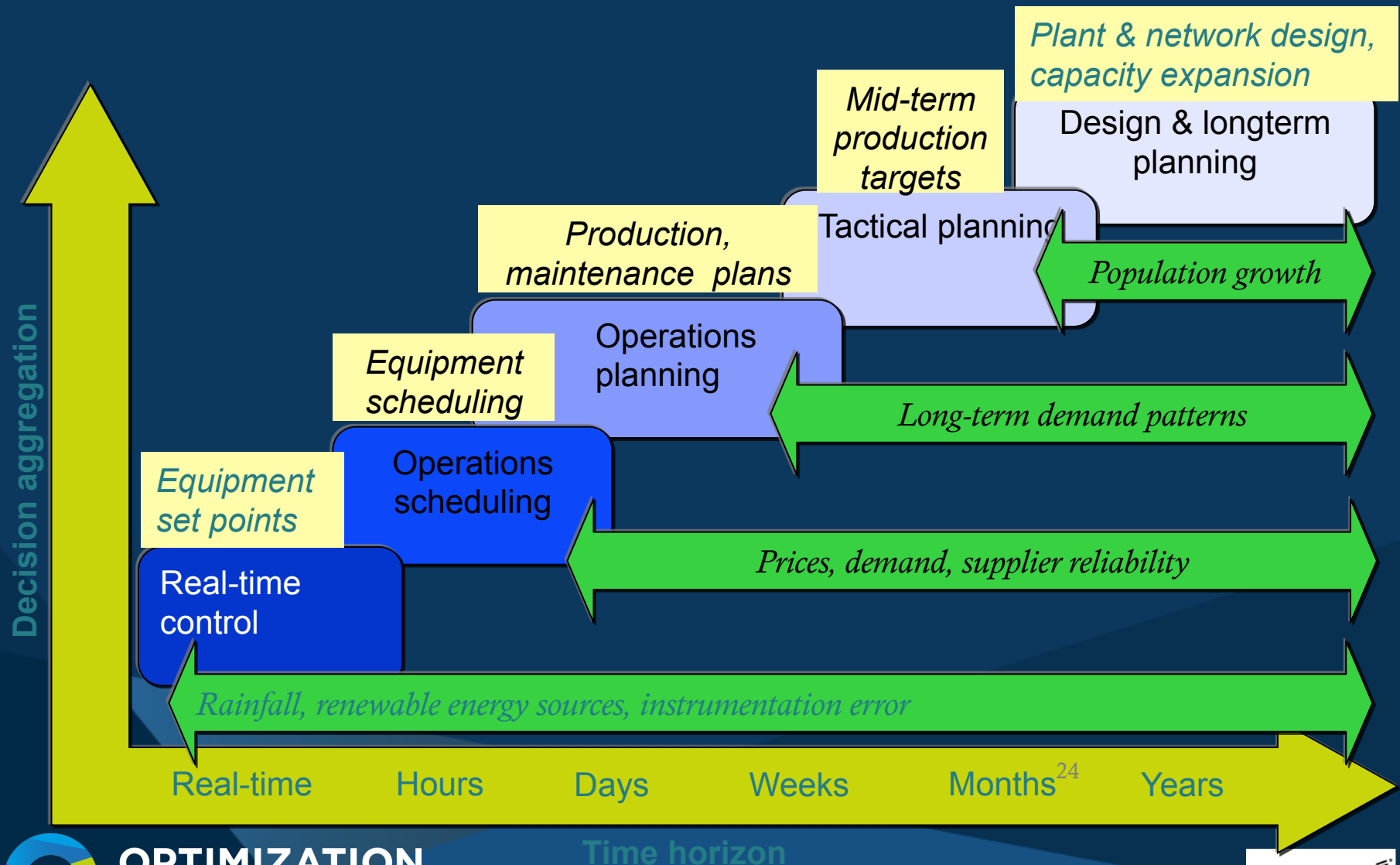
Examples of decisions



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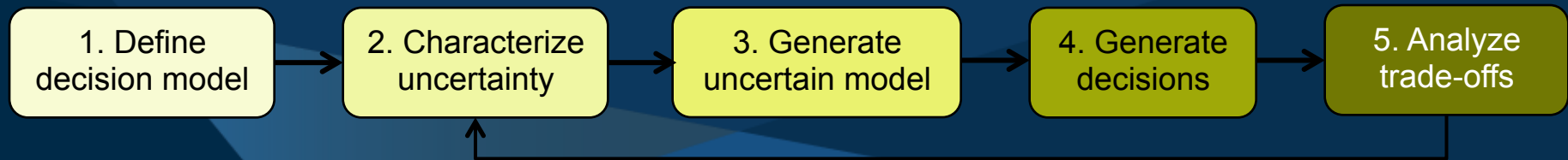


Impact of uncertainty



Uncertainty Toolkit goals

- 2013 Joint Program between IBM Research and Decision Optimization
- Goals
 - Increase customer solution resilience, reliability, and stability
 - Improve trust & understanding of optimization technology
- Our approach
 - Leverage Decision Optimization & mathematical optimization to hedge against uncertainty (e.g. uncertain demand, task durations, prices, resource availability)
 - A user-friendly toolkit as plug-in to Decision Optimization Center
- *5 steps to resilient decisions in the face of uncertainty*



Stable decisions, stable profits

- Test examples
 - Supply chain planning for a motorcycle vendor
2% increase in profits vs. deterministic optimization
 - Inventory optimization for IBM Microelectronics Division
Greater than 7x increase in feasibility vs. deterministic optimization
- Case studies
 - Energy cost minimization for Cork County Council
Estimated 30% value-add in cost reduction vs. deterministic optimization
 - Leakage reduction for Dublin City Council
Estimated 10 times increased stability vs. deterministic optimization
- Other benefits
 - Automated toolkit reduces dependence on PhD-level experts & statistical data
 - Visualize trade-off between multiple KPIs across multiple scenarios and plans²⁶

Effect of data uncertainty on decision resilience

"Resilient"
how decisions should be

re·sil·ient¹

adjective \ri-'zil-yənt\
a : capable of withstanding shock without permanent deformation or rupture

b : tending to recover from or adjust easily to misfortune or change

"Veracity"
the data quality decision makers and decision software often assume

ve·rac·i·ty¹

noun \və-'ra-sə-tē\
: truth or accuracy

"Uncertain"
the actual data quality

un·cer·tain¹

adjective \,ən-'sər-tən\
: not exactly known or decided : not definite or fixed

: not sure : having some doubt about something



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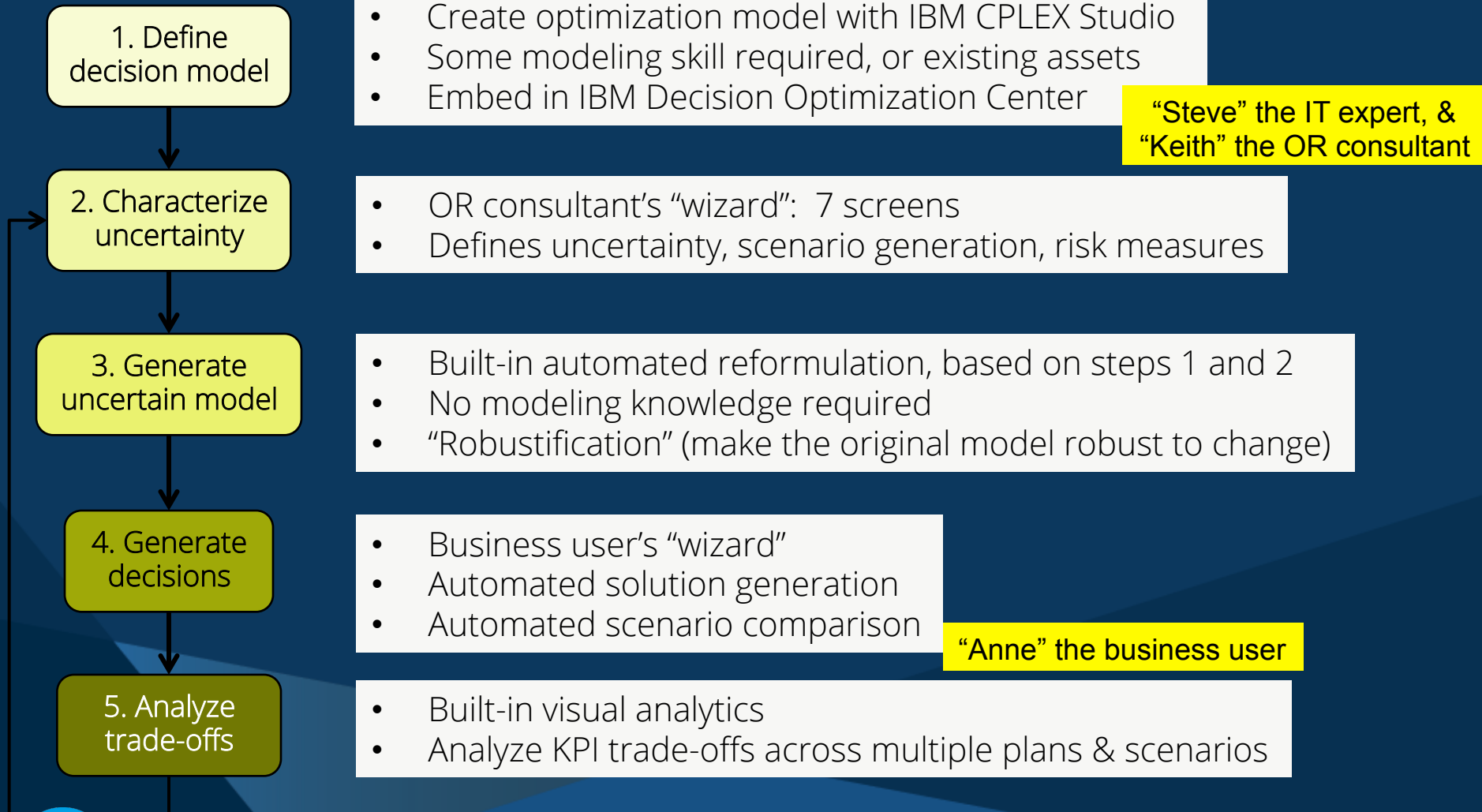
Assuming data veracity in the face of uncertainty leads to decision instability, as well as distrust in decision optimization technology.

Example use cases for the Uncertainty Toolkit

Industry	Typical company	Problem type
Government	Government agencies	Project portfolio management
Tourism	Hotel operators, Airlines	Revenue management
Transport	Railroads	Railroad locomotive planning
Transport	Supermarket chain, cement	Delivery / pick-up truck routing
Utilities	Electricity company	Production planning
Utilities	Water company	Tactical reservoir planning
Utilities	Water company	Water distribution network configuration
Utilities	Electricity company	Unit commitment
Utilities	Water network operators	Pump scheduling
Utilities	Water network operators	Pressure management
Utilities	Electricity company	Energy trading
Oil and gas	Oil company	Vessel scheduling
Manufacturing	Manufacturer	Operational project scheduling
Manufacturing	Car manufacturer	Manufacturing line load balancing
Manufacturing	Aircraft manufacturer	Plant assembly
Manufacturing	Car manufacturer	Sales and operations planning
Supply chain	Manufacturer	Contractor to transport leg assignment
Supply chain	Manufacturer	Product to store allocation
Supply chain	Manufacturer, oil&gas	Inventory optimization
Supply chain	Manufacturer, oil&gas	Supply chain network configuration
Supply chain	Manufacturer	Procurement planning
Supply chain	Manufacturer	Emergency operations planning
Commercial	Banks, insurance, TV	Marketing campaign optimization
Finance	Banks	Collateral allocation



5 steps to resilience with the Uncertainty Toolkit



Uncertainty Toolkit: automated reformulations

Robust / Stochastic approach	Applicable model types	Resulting model types	Uncertainty characterization	Restrictions
Single-stage penalty approach (<i>Mulvey et al., 1995</i>)	LP MILP	LP (or QP) MILP (or MIQP)	Scenarios (finite)	No uncertain data in objective function
Two-stage penalty approach (<i>Mulvey et al., 1995</i>)	LP MILP	LP (or QP) MILP (or MIQP)	Scenarios (finite)	No uncertain data in objective function
Multistage Stochastic (e.g. <i>King & Wallace, 2012</i>)	LP MILP	LP MILP	Scenarios (finite)	None
Safety margin approach with ellipsoidal uncertainty sets (<i>Ben-Tal & Nemirovski, 1999</i>)	LP MILP	QCP MIQCP	Range	No uncertain data in standalone parameters or equality constraints
Safety margin approach with polyhedral uncertainty sets (<i>Bertsimas & Sim, 2004</i>)	LP MILP	LP MILP	Range	No uncertain data in standalone parameters or equality constraints
Extreme Scenario approach (<i>Lee, 2014</i>)	LP MILP	LP MILP	Range	No uncertain data in variable coefficients
Distributionally robust reformulation (<i>Mevisen et al., 2013</i>)	LP MILP	LP MILP	Scenarios	Uncertainty in standalone parameters handled as penalty term in objective



Uncertainty Toolkit: automated reformulations

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Two-stage penalty approach	LP	LP (or QP)	Scenarios	No uncertain data in

Q: How do I know which of these methods to use?

A: The Uncertainty Toolkit will decide automatically based on your input into the Consultant's Wizard

Safety margin approach with ellipsoidal uncertainty sets (<i>Ben-Tal & Nemirovski, 1999</i>)	LP MILP	QP MIQCP	Range	No uncertain data in standalone parameters or equality constraints
Safety margin approach with polyhedral uncertainty sets (<i>Bertsimas & Sim, 2004</i>)	LP MILP	LP MILP	Range	No uncertain data in standalone parameters or equality constraints
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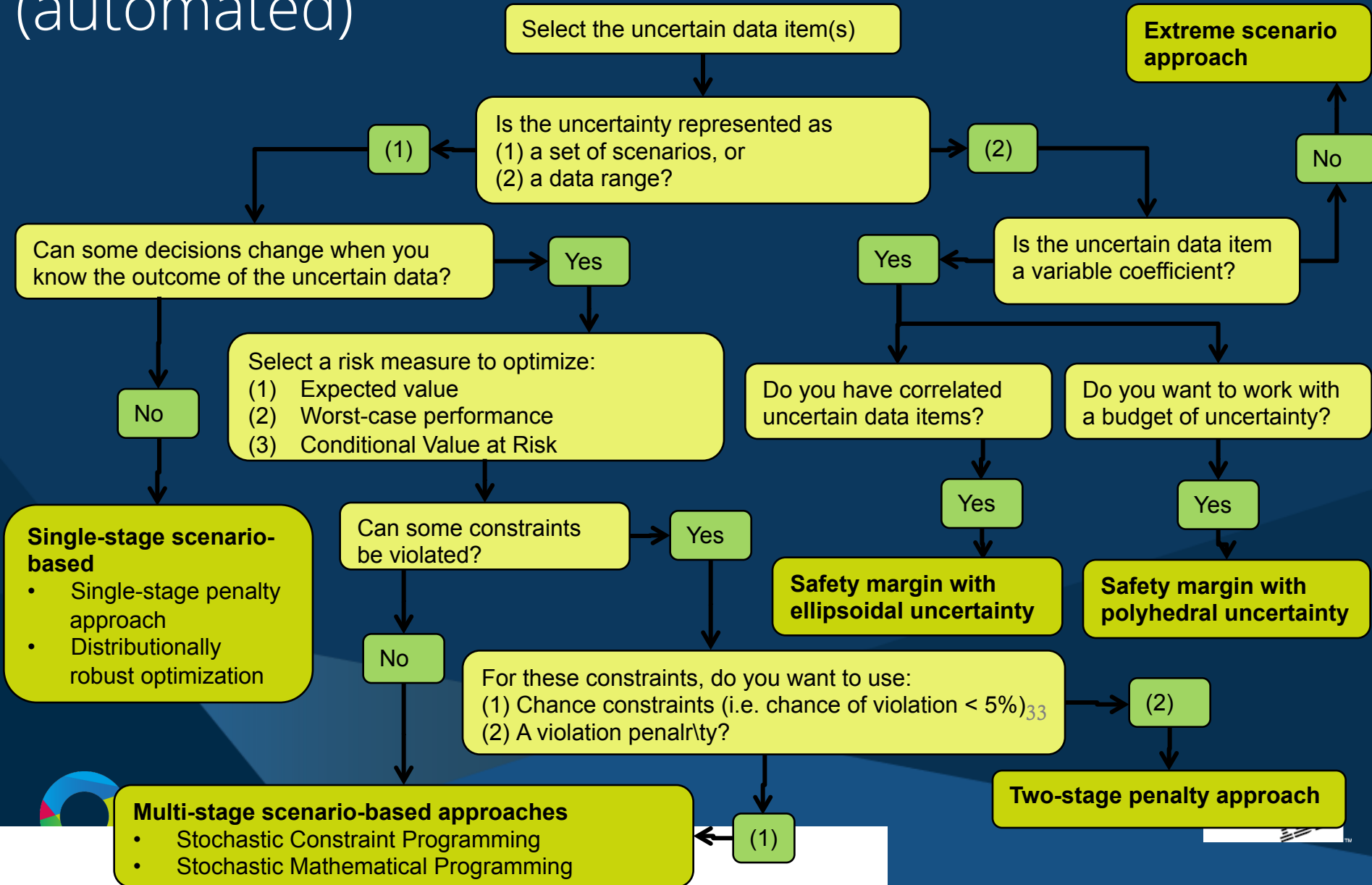


Questions

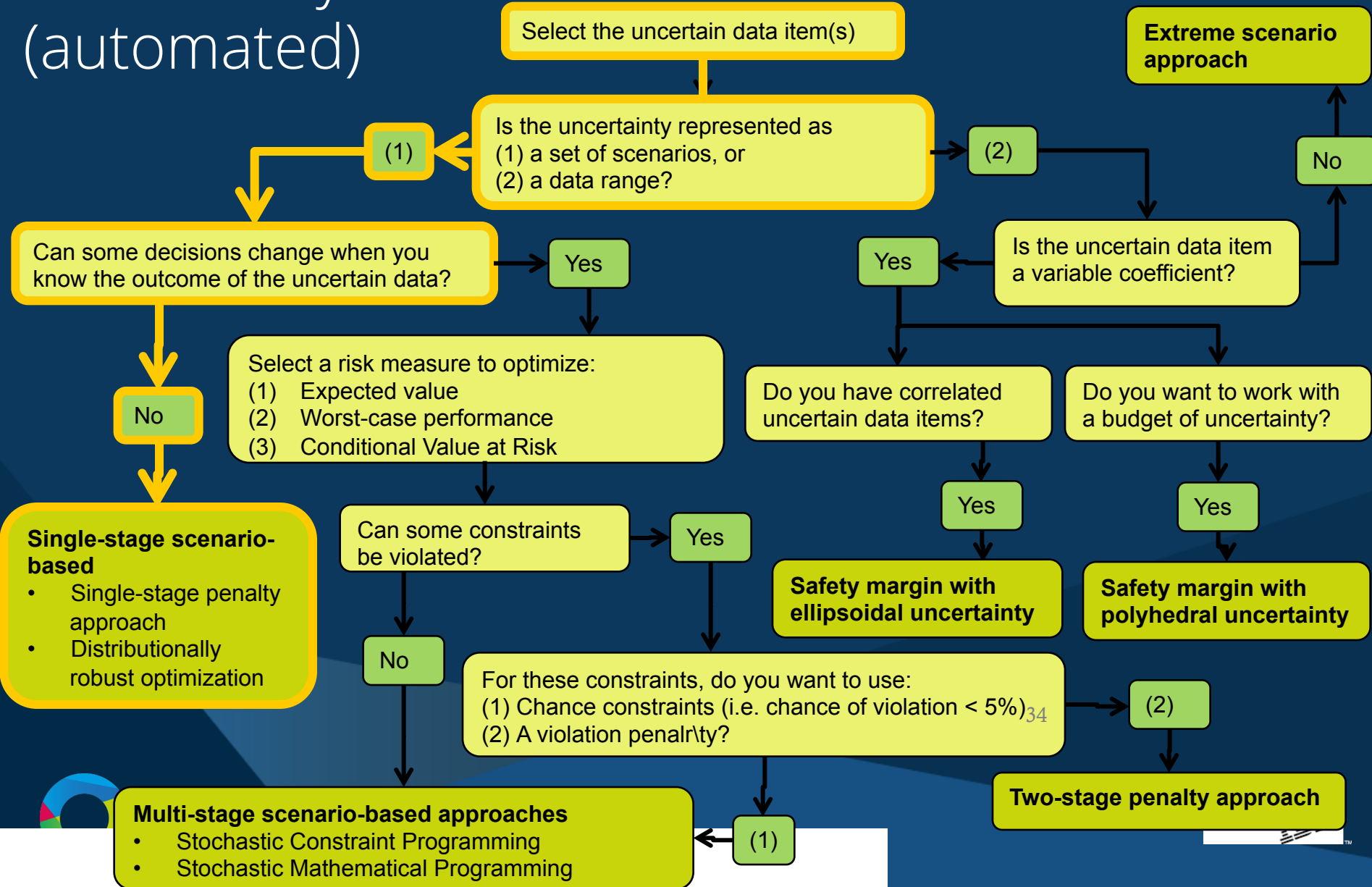
- What is the right model?
- Can we automate the selection of the model?

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Uncertainty Toolkit Decision Tree (automated)



Uncertainty Toolkit Decision Tree (automated)

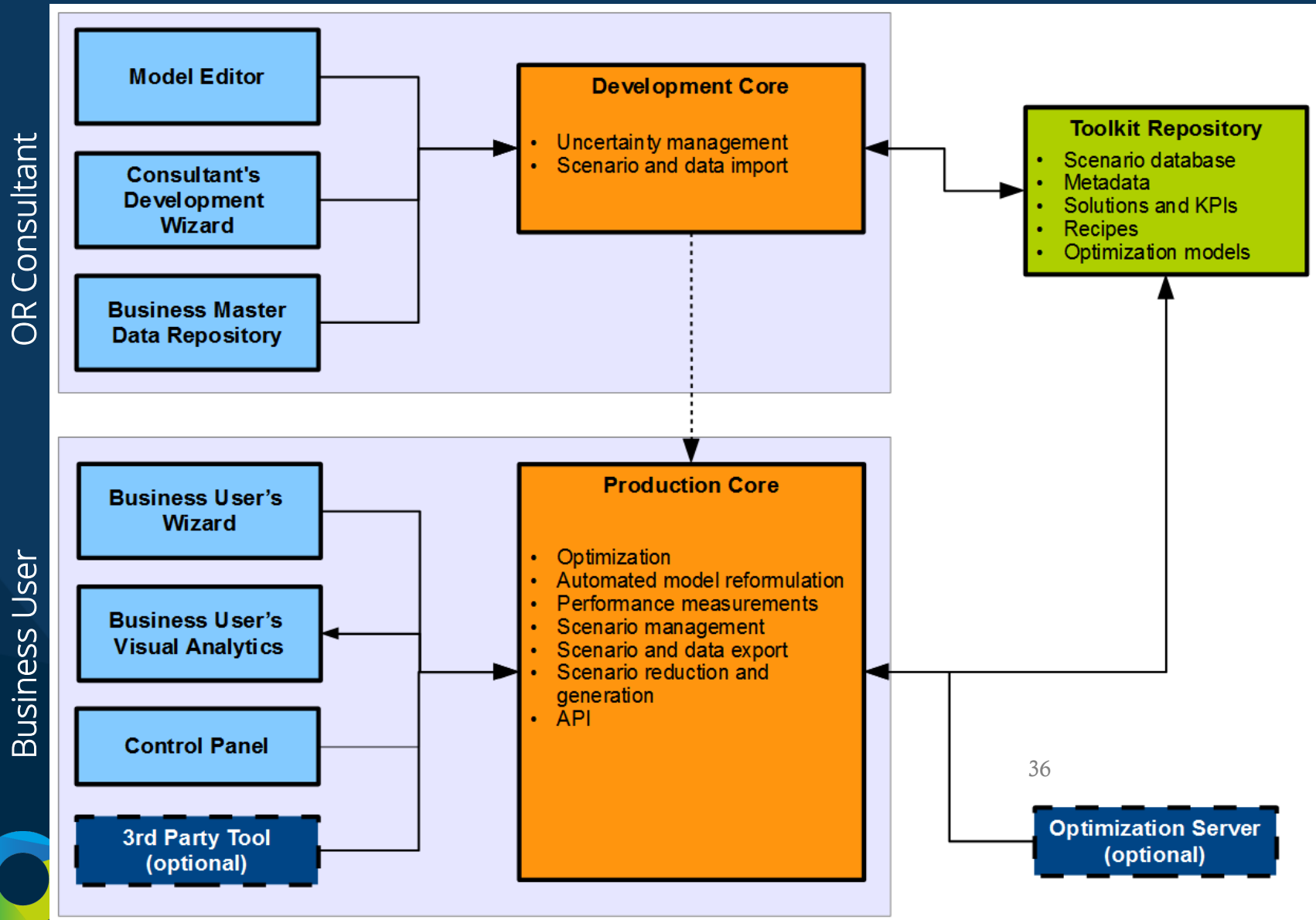


Question:

- What is the architecture?

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Uncertainty Toolkit architecture



Question

- Can I automate the reformulation from the deterministic model?

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Example: Automated model reformulation for stochastic CP

```
18
19 dvar interval task[i in 1..n] size TaskDuration[i];
20 dvar sequence seq in task types all(i in 1..n) i;
21 dexpr int station[i in 1..n] = startOf(task[i]) div c;
22
23 minimize 1+max(i in 1..n) station[i];
24 subject to {
25   noOverlap(seq, Setups);
26   forall (p in Precedences)
27     endBeforeStart(task[p.pred], task[p.succ]);
28   forall (i in 1..n)
29     station[i] == (endOf(task[i]) - 1) div c;
30 };
31 |
```

Input: Deterministic model

Automated model reformulation

Output: Stochastic model

```
39
40 dvar interval task[i in 1..n][s in Scenarios] size TaskDuration[i][s];
41 dvar sequence seq[s in Scenarios] in all(i in 1..n) task[i][s] types all(i in 1..n) i;
42
43 dexpr int station[i in 1..n][s in Scenarios] = startOf(task[i][s]) div c;
44
45 minimize sum(s in Scenarios) Probability[s]*(1 + max(i in 1..n) station[i][s]);
46 subject to {
47
48   forall (s in Scenarios) {
49     noOverlap(seq[s], Setups);
50     forall (p in Precedences)
51       endBeforeStart(task[p.pred][s], task[p.succ][s]);
52     forall (i in 1..n)
53       station[i][s] == (endOf(task[i][s]) - 1) div c;
54   }
55
56   forall (s in 1..(S-1), i in 1..n) {
57     typeOfNext(seq[s], task[i][s], -1) == typeOfNext(seq[s+1], task[i][s+1], -1);
58   }
59 };
60
61 |
```

Question

- What is the right Software Platform?

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Decision Optimization Center (DOC) is about Decision Support

- DOC for OR (Operations Research) experts: Eclipse-based development environment to create optimization solutions
 - CPLEX Studio embedded for OR needs
 - Data modeling & connections
 - Visualization
 - Custom Java extensions
- DOC for business users: Supports decision making leveraging optimization
 - Scenario-based analysis
 - Manual planning in addition to optimization
 - Alternative business goals
 - Business rules
 - Tradeoff visualization
 - “Freeze” partial solution and solve again

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Decision Optimization Center IDE

OPL Model Development

The screenshot displays the Eclipse IDE with the Decision Optimization Center (DOC) plugin. The main editor shows the `CustomAction.java` file, which implements the `IloCustomActionHandler` interface. The code includes package declarations, imports, and methods for registering mappings, getting settings files, and getting resource files. The `doAction2()` method is also visible.

The left sidebar shows the Project Explorer with a tree view of the project structure, including folders like `NurseMultiModel`, `Nurses_odm`, and `warehouse`. The Variables view shows a table of variables and their values.

The bottom panel contains the Performance Monitor, which displays statistics for the Cplex solver. The table below shows the current statistics:

Estadística	Valor
Cplex	
Restricciones	250
Variables	10051
Binary	50
Coeficientes distintos de cero	20050
MIP	
Objetivo	1,448,142857
Principal	1,480
Nodos	141
Nodos restantes	86
Iteraciones	1636

The Performance Monitor also includes a graph showing the progress of the solver over time (seconds). The graph displays three lines: `Mejor entero` (green), `Mejor nodo` (red), and `Solución entera` (yellow). The `Mejor entero` line shows a steady decrease in the objective value over time, while the `Mejor nodo` and `Solución entera` lines remain relatively flat.

Decision Optimization Center IDE

Configuration of built-in visualization

The screenshot displays the Eclipse IDE interface for the Decision Optimization Center. The main window is titled "OPL - SupplyDemand/SupplyDemand_views.odm.vw - Eclipse SDK". The interface is divided into several panes:

- Left Pane:** Contains a project explorer showing the "Proyectos OPL" and a list of files including "AccionesComerciales2", "CustomAction", "DBTool", "DiagrammerView", "ExampleCanal", "ExportODMData", "JIRAs", "NurseMultiModel", "Nurses_odm", "ProgressBar", "ScenarioUpdater", "ServiceAPIExample", "SupplyDemand (New S&OP demo)", "TestProject", and "warehouse (A warehouse location model)".
- Top Center Pane:** Shows the "SupplyDemand" project structure with folders like "Analysis", "Input Data", "Products", "Market", "Plants and Capacities", "Inventory", and "Misc".
- Right Pane:** Displays the "Plant Capacities" configuration. It includes a table for "Tablas de gráficos" and a "Configuración de gráfico" section.

Table: Tablas de gráficos

Índice	Tabla	Columna	Etiqueta	Clave
0	PlantMonthCapacities	value (Entero)	Capacities	Months

Configuración de gráfico

- Datos:** ☒ Todo, ☐ Blindexado, ☐ Monoindexado
- Tabla:** PlantMonthCapacities, **Columna:** value (Entero)
- X desde:** Months
- Gráfico para cada uno:** ☒ Plants
- Modo:** Valor por clave
- Etiqueta:** Capacities
- Color:** Automático

Opciones del área de vista previa

Todas las áreas de vista previa están usando datos generados por OPL IDE.

Configuración de usuario de ODM

Cerrar ODM y guardar configuración

Bottom Pane: Shows a table with columns "Línea", "Original", "Relajada", and "Elemento".

Page Number: 42

Decision Optimization Center IDE

Custom Java extensions

Java - CustomAction/src/action/CustomAction.java - Eclipse SDK

File Edit Source Refactor Navigate Search Project Run Window Help

Package Explorer

- AccionesComerciales2
 - CustomAction
 - src
 - action
 - CustomAction.java
 - workerServiceTechUserNa
 - CustomAction(IloODMAppli
 - actionEnabled(Action)
 - doAction()
 - doAction2()
 - doAction3()
 - getDataListener()
 - getResourceFiles()
 - getSettingsFiles()
 - makeValidCopyName(IloSo
 - registerMappings(IloMessa
- OpenView.java
- JRE System Library [jre1.5.0_06]
- Referenced Libraries
- classes
- Data
- deploy
- resources
- build.xml
- CustomAction_deployment_dev.odmnd
- CustomAction_deployment_prod.odmnd
- CustomAction_mapping.dat
- CustomAction_optimmodel.odmm
- CustomAction_relationalmodel.odmm
- CustomAction_start_mapping.dat
- CustomAction_views.odmmw
- CustomAction.dat
- CustomAction.mod

DBTool

DiagrammerView

ExampleCanal

ExportODMData

JIRAs

NurseMultiModel

Nurses_odm

ProgressBar

ScenarioUpdater

ServiceAPIExample

SupplyDemand

TestProject

test.mod

test.ops

warehouse

```
package action;

import ilog.odm.datasvc.IloDataException;

public class CustomAction extends IloCustomActionHandler{

    static private final String workerServiceTechUserName = "workerService";

    public CustomAction(IloODMApplication application, IloCustomActionDescription desc) {
        super(application, desc);
    }

    @Override
    public void registerMappings(IloMessageMapper mapper) {
        mapper.registerActionMethod("doAction", "doAction");
        mapper.registerActionStateMethod("doAction", "actionEnabled");
    }

    @Override
    public String[] getSettingsFiles() {

        return new String[] { "customAction.xml", "InsertCustomAction.xml" };
    }

    public String[] getResourceFiles() {
        return new String[] { "customAction" };
    }

    /*
     * Test to use the processing service
     */
    public void doAction2() {
```

Problems 24 errors, 120 warnings, 0 others (Filter matched 124 of 144 items)

Description	Resource	Path	Location	Type
Errors (24 items)				
Warnings (100 of 120 items)				

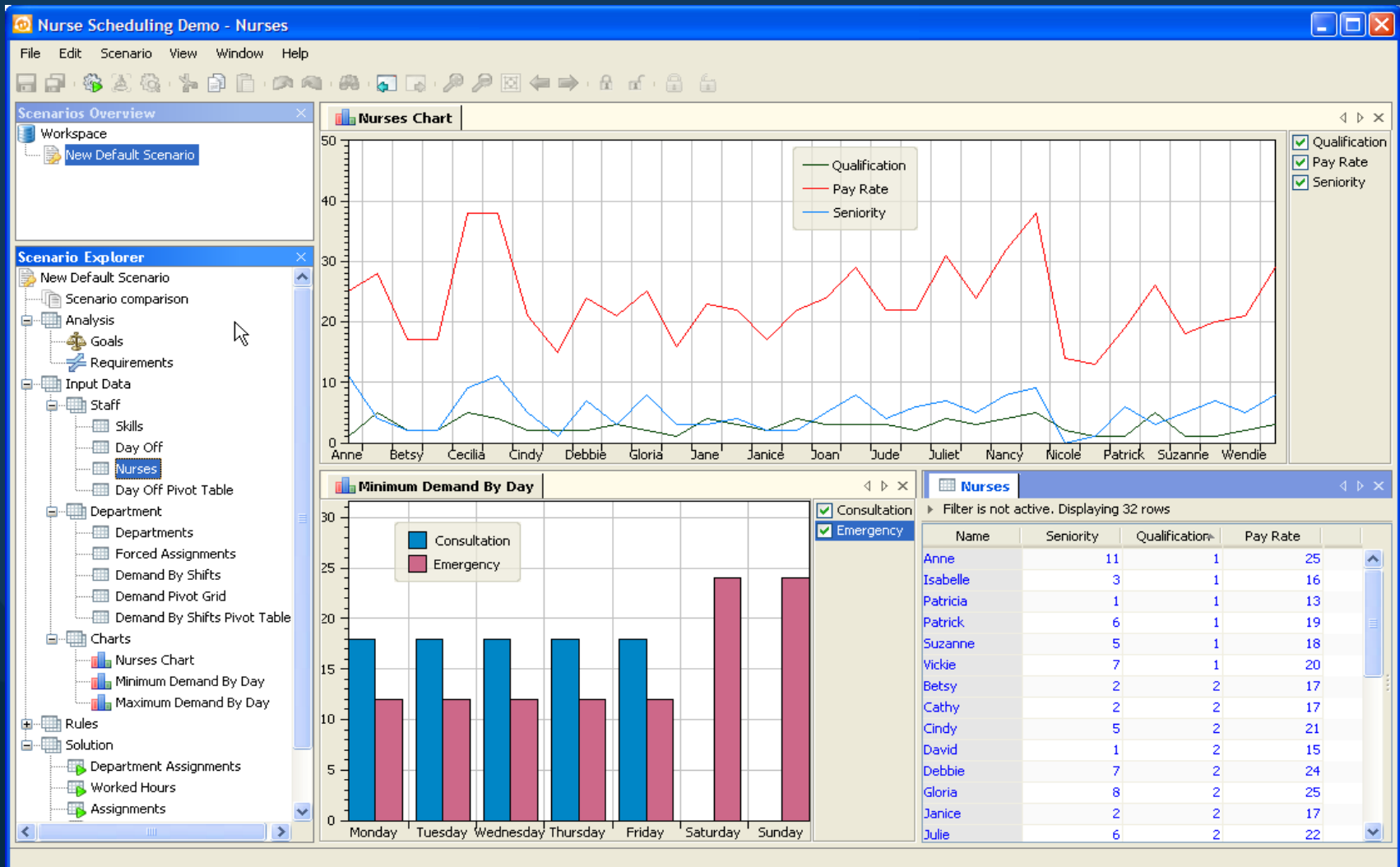
43

start Error: Ac... 2 Micro... Skype™ ... Comman... 2 Wind... G:\prote... 3 Micro... Java - C... ES VS 57 15:39

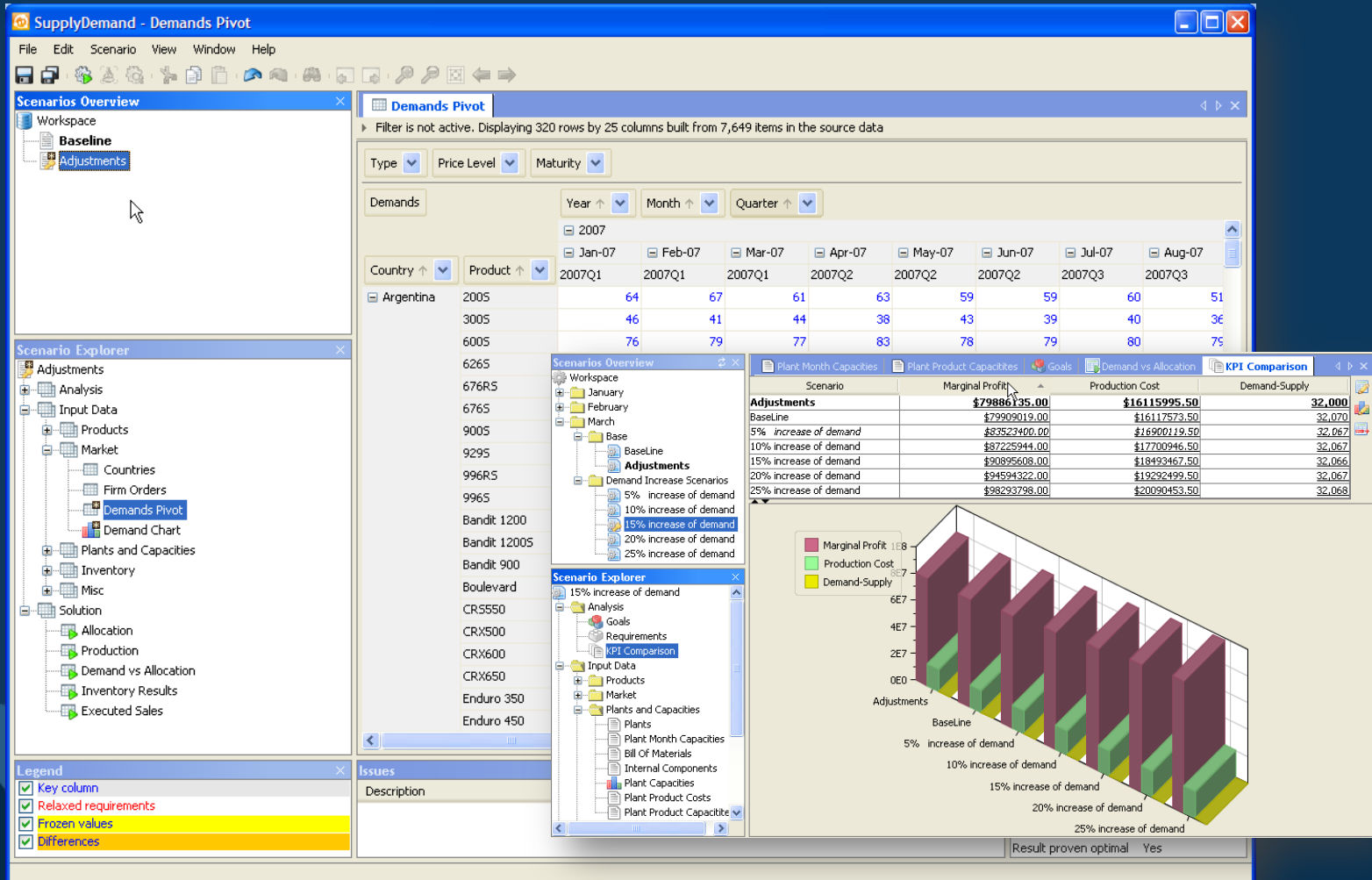
00:00:07:46

Business Partner IBM

Displays using Simple Tables and Charts – out of the box



Pivot Tables and Scenario Comparison – out of the box



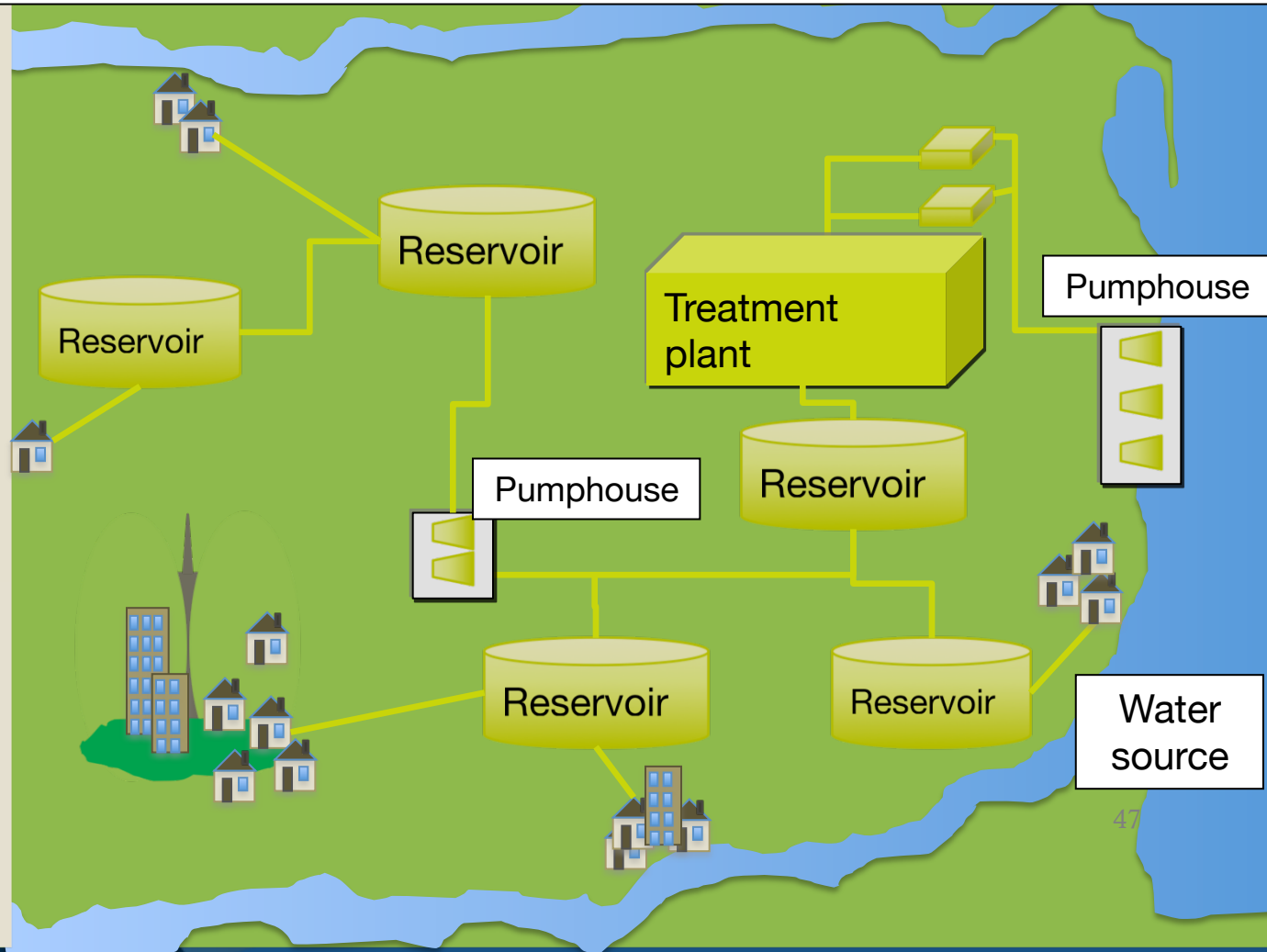
Case study: Water treatment/distribution energy cost reduction

- Big picture: Cork County Council must reduce energy consumption by 20% by 2020
- 95% of this utility's water-related energy costs due to pump operations
- New dynamic energy pricing schemes leverage renewables (wind energy)
- Trade-off: Cleaner energy at lower prices, but uncertainty in price due to
 - Wind uncertainty
 - Network outages
 - Other weather conditions
- Goal: Schedule pumps leveraging dynamic prices, while hedging against uncertainty in price prediction

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Simplified network (illustration purposes)

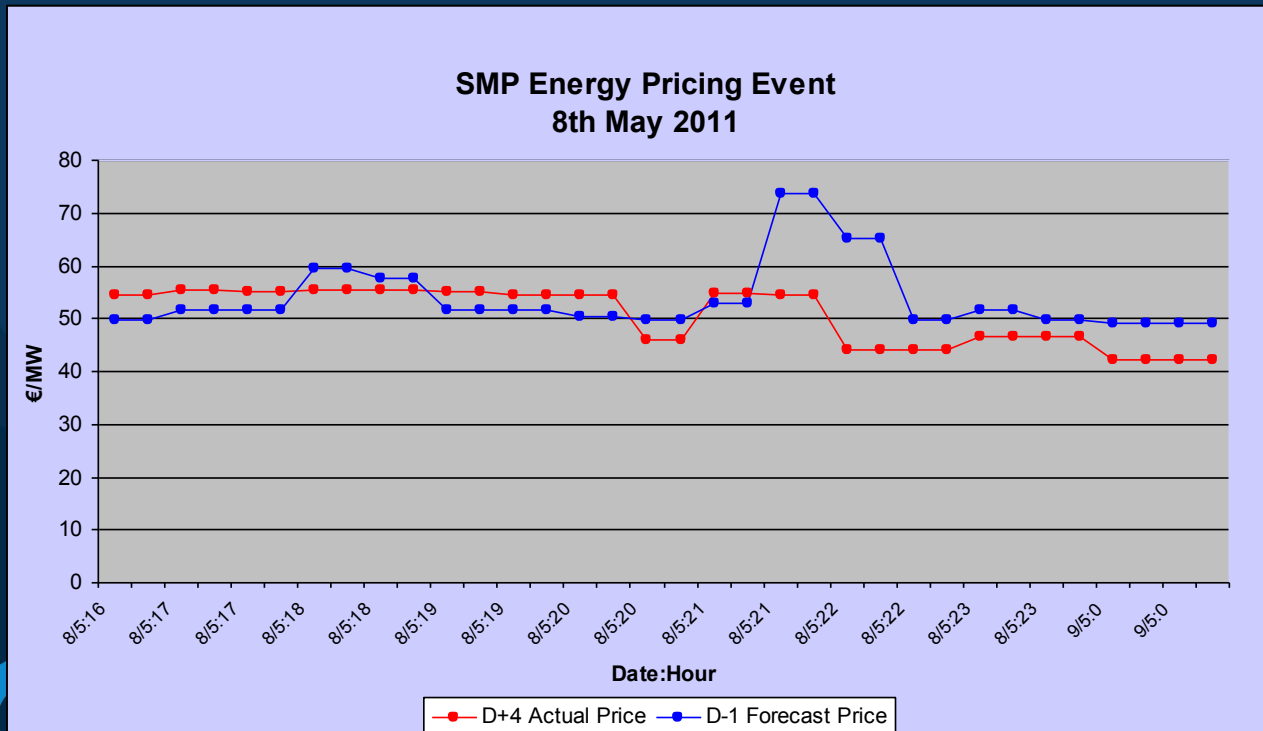
Goal: Optimize pump schedules to minimize (uncertain) energy costs while meeting demand and respecting plant and network constraints*



* Based on Cork County Council's Inniscarra network

Uncertainty in price prediction

- Forecasted (D-1) post ante price from supplier
 - Considers forecasted demand based on weather, special events, wind, etc.
- Actual (D+4) price charged 4 days after the event
 - Forecasted (D-1) and Settled price (D+4) can differ due to changes in predicted wind energy availability, weather, and unpredicted grid events



Question:

Should utility switch to a dynamic pricing scheme?

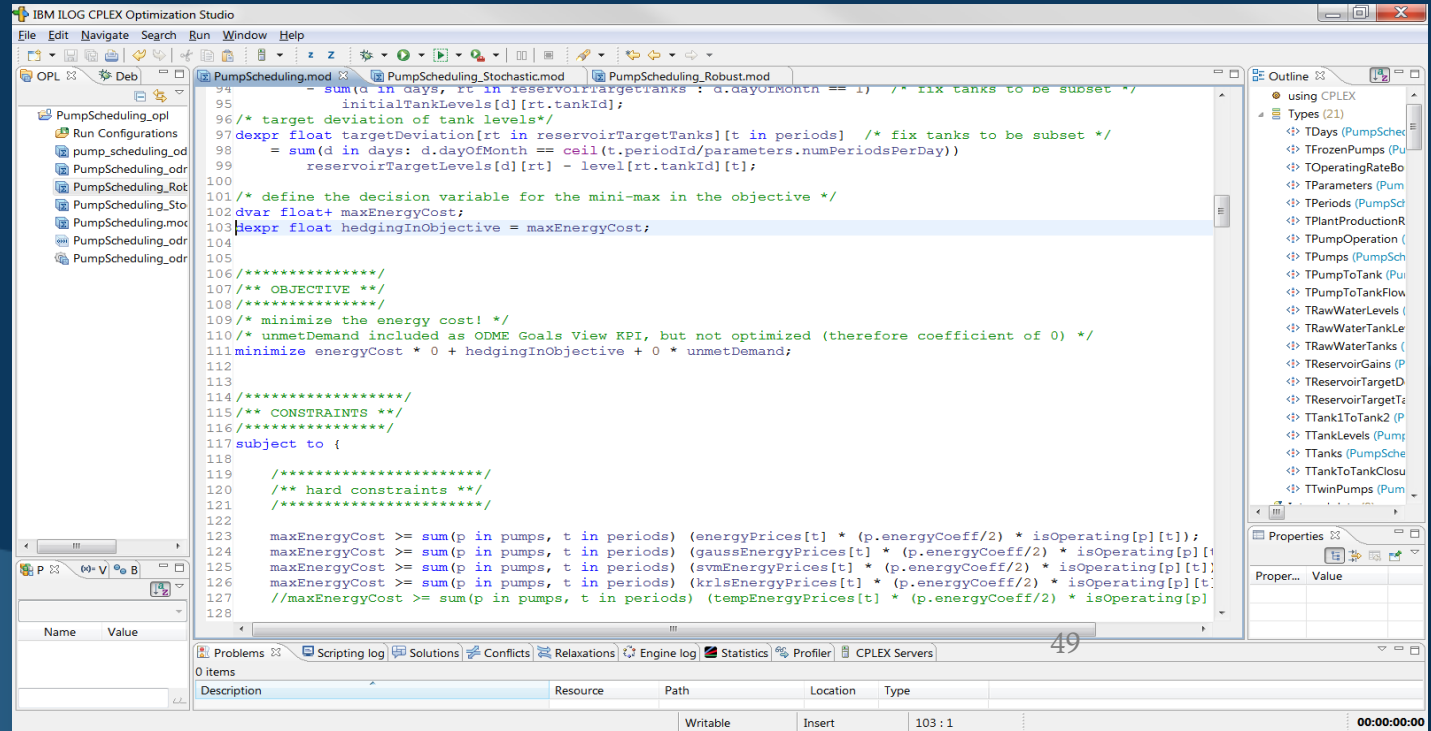
Step 1: Prove dynamic pricing benefits

Step 2: Prove optimization benefits

Step 3: Deal with uncertainty

Step 1: Define decision model

- Define objective, decisions, constraints (mathematical modeling skill required)
 - Objective: minimize energy costs from pump operations
 - Decisions: when to switch pumps on/off (decided every 30 minutes for 24 hours in advance)
 - Constraints: satisfy tank levels, pump operation rules, customer demand, network constraints
- Model using CPLEX Studio, assuming certain data ("deterministic" model)



The screenshot displays the IBM ILOG CPLEX Optimization Studio interface. The main window shows a CPLEX model file named 'PumpScheduling.mod'. The model is written in CPLEX's modeling language (MPL) and includes the following key sections:

- Objective:** The model aims to minimize energy costs. The objective function is defined as:
`minimize energyCost * 0 + hedgingInObjective + 0 * unmetDemand;`
- Constraints:** The model includes constraints for tank levels, pump operation rules, and customer demand. The constraints are defined within a 'subject to' block.
- Decisions:** The model defines decision variables for pump operations, including 'maxEnergyCost' and 'hedgingInObjective'.

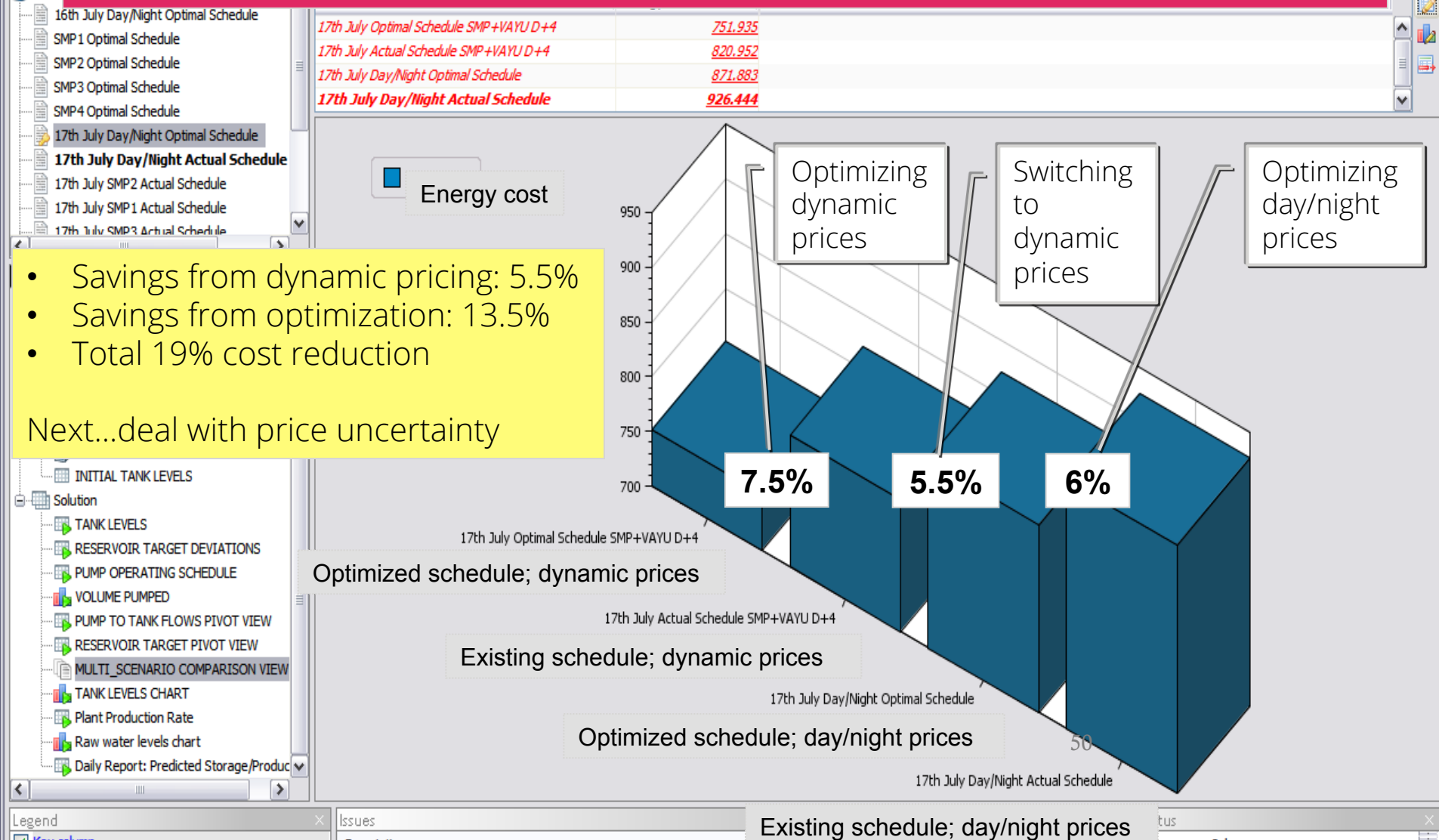
The interface also shows a project tree on the left with files like 'PumpScheduling.opl', 'PumpScheduling.odr', and 'PumpScheduling.mod'. The right pane shows the 'Outline' view with a list of model components, including 'Types (21)', 'TDays (PumpSche)', 'TFrozenPumps (Pu)', 'TOperatingRateBo', 'TParameters (Pum)', 'TPeriods (PumpSc)', 'TPlantProductionR', 'TPumpOperation (', 'TPumps (PumpSch', 'TPumpToTank (Pui', 'TPumpToTankFlow', 'TRawWaterLevels (', 'TRawWaterTankLe', 'TRawWaterTanks (', 'TReservoirGains (P', 'TReservoirTargetD', 'TReservoirTargetTs', 'TTank1ToTank2 (P', 'TTankLevels (Pump', 'TTanks (PumpSche', 'TTankToTankClosu', and 'TTwinPumps (Pum'. The bottom status bar shows '0 items' and '103:1'.

OPTIMIZATION

Business

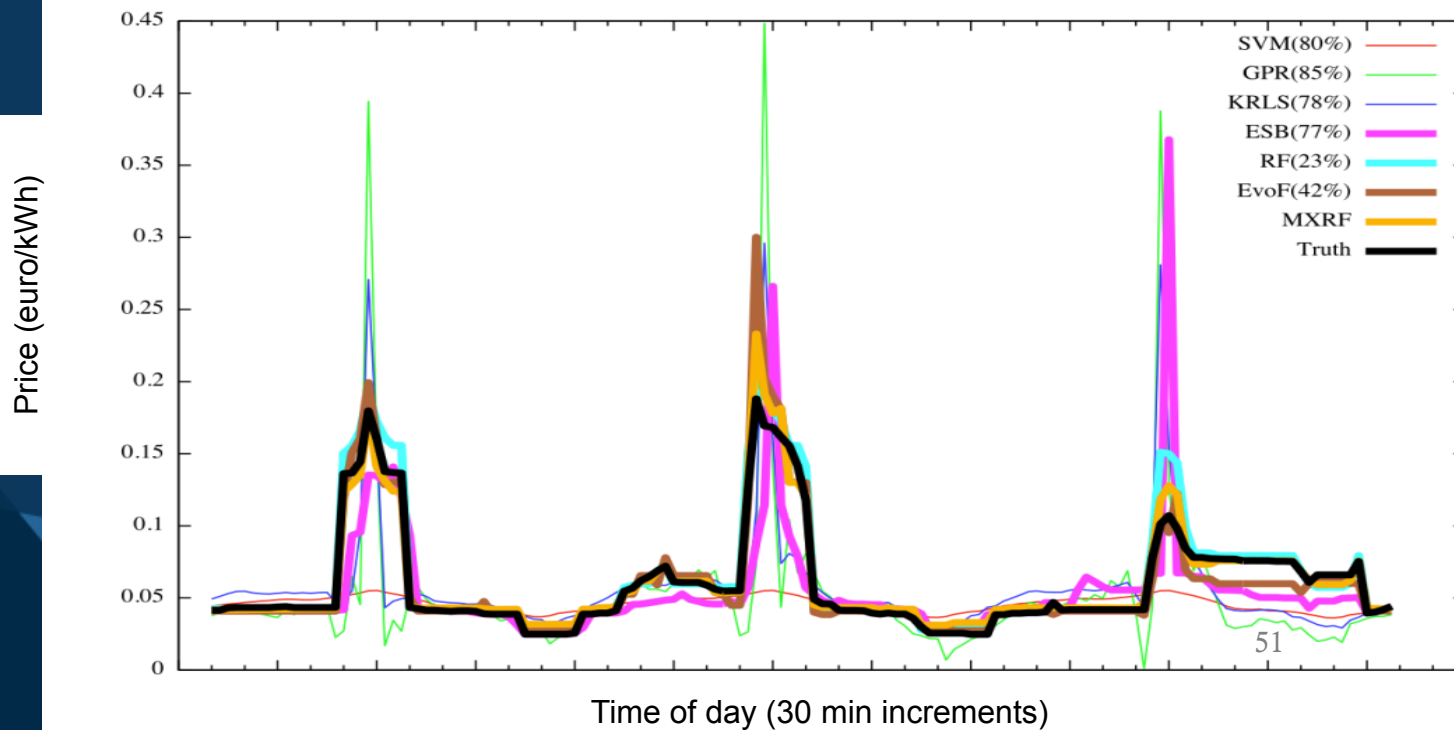
Note: When data is fairly certain, deterministic models are sufficient to provide significant benefit

Decision model in Decision Optimization Center prototype: Predicted energy cost savings from pump optimization and (known) dynamic energy prices



Step 2: Characterize uncertainty

- Price scenarios, with likelihoods:
 - From energy provider
 - From IBM Research forecasts



Step 2: Uncertainty Toolkit wizard for consultant input (1 of 2)

1. Select uncertain data

Uncertainty Toolkit: recipe manager

Select uncertain data items

Available data items

- AVG_COST_BY_PERIOD
- AVG_COST_BY_UNIT
- FROZEN_IN_USE
- MAINTENANCE_RULES
- MAX_PROD_RULES
- MUST_RUN_RULES
- MUST_TURN_OFF_RULES
- NO_PLANTS_ONLINE
- PARAMETERS
- PERIODS
- PRODUCTION
- RCTable_Maintenance Rule
- RCTable_Max Time in Use
- RCTable_Must Run Rules
- RCTable_Must Turn Off Rules

Uncertain data items

LOADS

Add >

< Remove

<< Clear

Back Next Finish Cancel



2. Select data scenarios vs. ranges

Uncertainty Toolkit: recipe manager

Select uncertain type

Select whether the uncertainty is captured as a data range, or by using discrete input data scenarios.

☒ Scenarios (discrete)

☐ ODME scenarios

☐ Extract from SPSS

☐ Range

Back Next Finish Cancel



3. Define decision stages

Uncertainty Toolkit: recipe manager

Define decision stages

How many decision stages, click

2

InUse	1
Production	2
TurnOn	1
TurnOff	1
SpinningCapacityTotal	2
ProductionTotal	2
SpinningReserveTotal	2

Back Next Finish Cancel



4. Select risk measures

Uncertainty Toolkit: recipe manager

Select risk measures to optimize

Use Optimize

☒ ☒ Expected value

☒ ☐ Worst-case outcome

☒ ☐ CVaR

Back Next Finish Cancel



Step 2: Uncertainty Toolkit wizard for consultant input (2 of 2)

Uncertainty Toolkit: recipe manager

Constraints should be

☐ Feasible for all scenarios

☒ Allowed to violate

Select all constraint may violate:

- ☒ meet_demand
- ☐ min_generation
- ☐ oper_max_generation
- ☐ max_generation
- ☐ init_ramp_up
- ☐ init_ramp_down
- ☐ ramp_up
- ☐ ramp_down
- ☐ min_up

Back Next Finish Cancel

5. Specify constraint satisfaction

Uncertainty Toolkit: recipe manager

KPI Selection

Configure the KPIs to evaluate in this recipe

KPI #1: OBJECTIVE_VALUE

Objective Value ☒ min problem?

KPI.ObjVar

KPI #2: INFEASIBILITY_MEASURE

Infeasibility Measure

KPI.ExpectedInf

KPI #3: OTHER

SpinningTotal ☐ min problem?

SpinningTotal

Back Next Finish Cancel

6. Define KPIs

Uncertainty Toolkit: recipe manager

Recipe Manager

Open recipes folder

Reload recipes list

Recipe availables

	Name	Description	Open	Delete
2014/03/13 11:31	Bental	new approach	Open	Delete
2014/03/13 11:27	Deterministic	simple cross comparison	Open	Delete
2014/03/13 11:29	Deterministic	with 7 KPIs	Open	Delete
2014/03/13 11:29	Extreme Scenario	description	Open	Delete
2014/03/19 15:39	recipe	description	Open	Delete
2014/03/19 15:54	recipe	description	Open	Delete
2014/03/11 15:23	Robust	Mulvey approach with 2+...	Open	Delete
2014/03/13 11:31	Stochastic 3	CVar	Open	Delete
2014/03/13 11:28	Stochastic Mulvey	mixed recipe	Open	Delete
2014/03/11 14:29	Stochastic	With 2 + 3 kpis	Open	Delete
2014/03/13 11:31	Stochastic	Worst case opt	Open	Delete

Back Next Finish Cancel

8. Save your recipe for later use

Uncertainty Toolkit: recipe manager

Is there any strong correlation between the parameters?

☒ Yes, take correlation into account

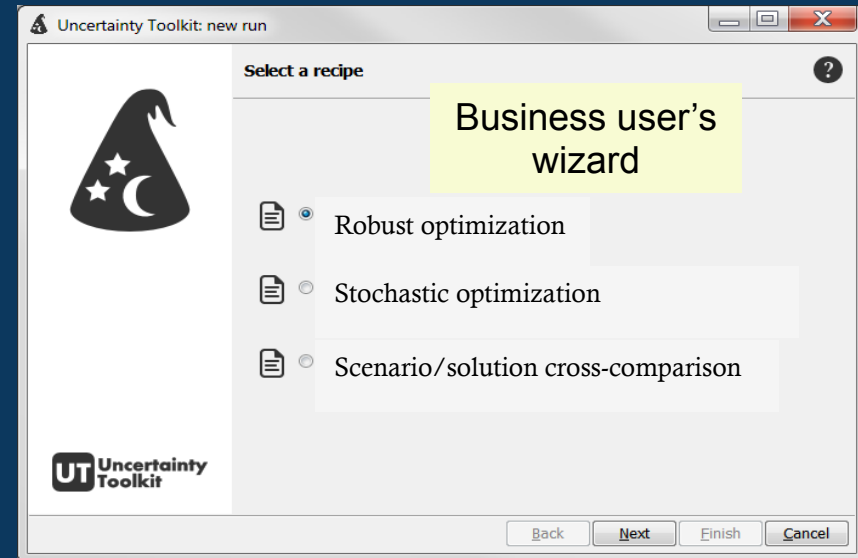
☐ No, allocate budget of uncertainty (across uncertain parameters)

Back Next Finish Cancel

7. Define correlation (optional)

Step 3: Generate uncertain model

- Uncertainty Toolkit automatically generates the uncertain model(s) depending on choices in Steps 1 and 2
- Uncertain models are typically classified as
 - “Robust”: hedging against worst case outcome(s)
 - “Stochastic”: optimizing for expected outcome(s)
 - If choice unclear, use both & visualize trade-offs

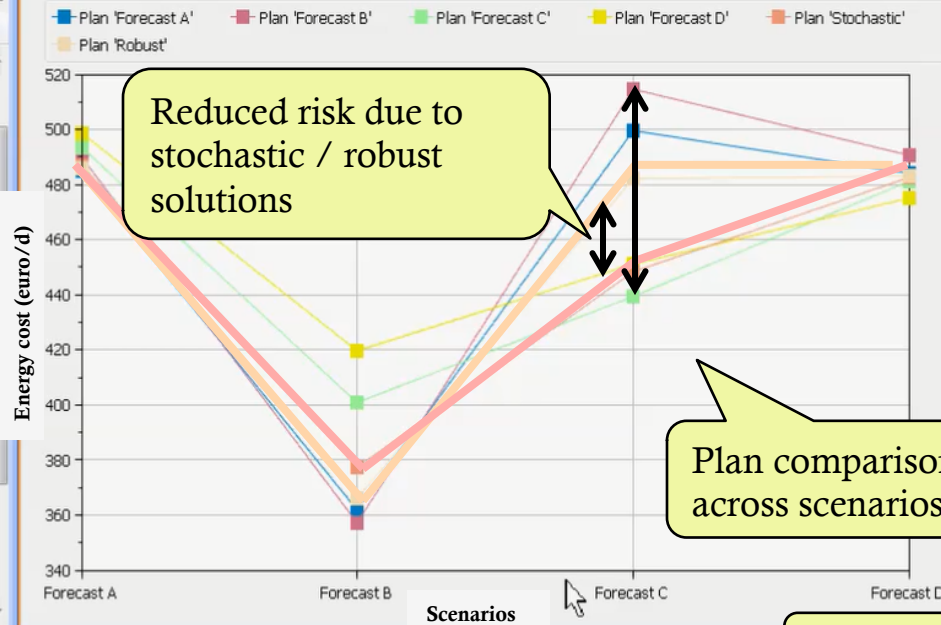


Step 4: Generate plans

- Uncertainty Toolkit generates multiple solutions (deterministic, robust, stochastic)
- Uncertainty Toolkit automatically does solution-scenario cross-comparison⁵⁴
 - What is the impact of change on each plan

Step 5: Analyze trade-offs

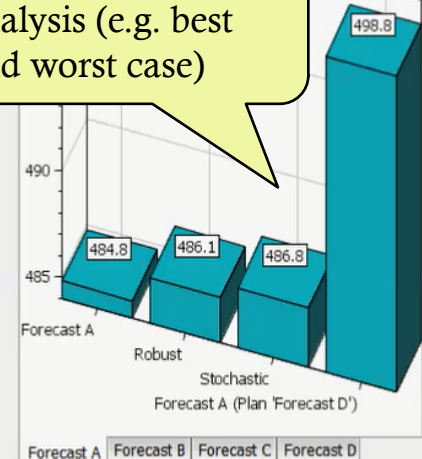
Automated plan generation for varying scenarios



Reduced risk due to stochastic / robust solutions

Plan comparison across scenarios

Scenario drill-down analysis (e.g. best and worst case)



Trade-off analysis across scenarios

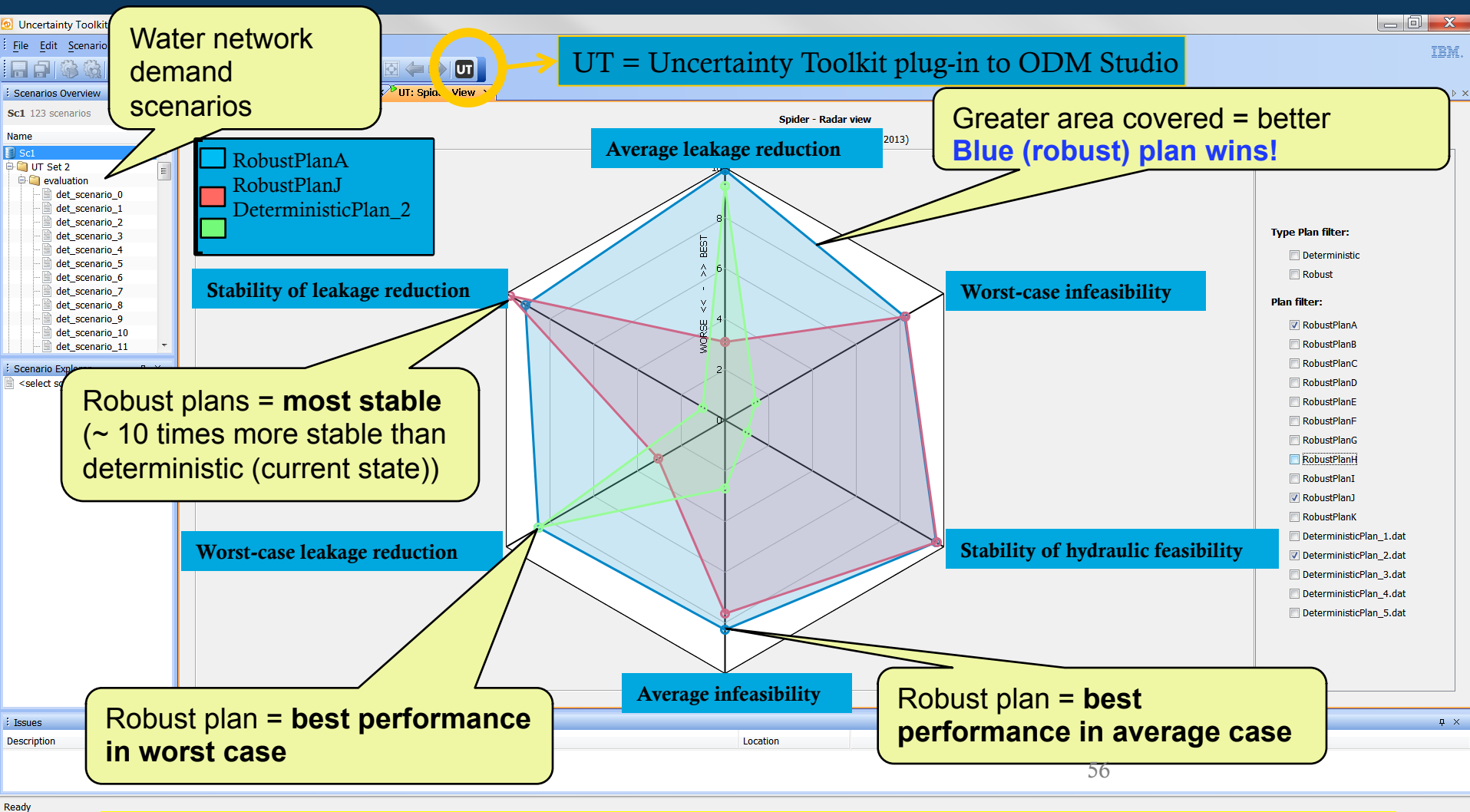
Plan	Forecast A	Forecast B	Forecast C	Forecast D	Average	Worst
Plan 'Forecast A'	484.8	361.9	499.4	484.1	457.6	499.4
Plan 'Forecast B'	489.7	357.0	514.7	490.5	463.0	514.7
Plan 'Forecast C'	493.6	400.9	439.6	481.1	453.8	493.6
Plan 'Forecast D'	498.8	419.9	451.4	475.1	461.3	498.8
Plan 'Stochastic'	486.8	377.6	448.8	486.1	452.1	486.8
Plan 'Robust'	486.1	366.3	448.1	486.1	452.1	486.1

Best average performance (stochastic model)

Best worst-case performance (robust model)

Pump scheduling use case:
Value-add from Uncertainty Toolkit
~ 30% improvement in energy cost reduction

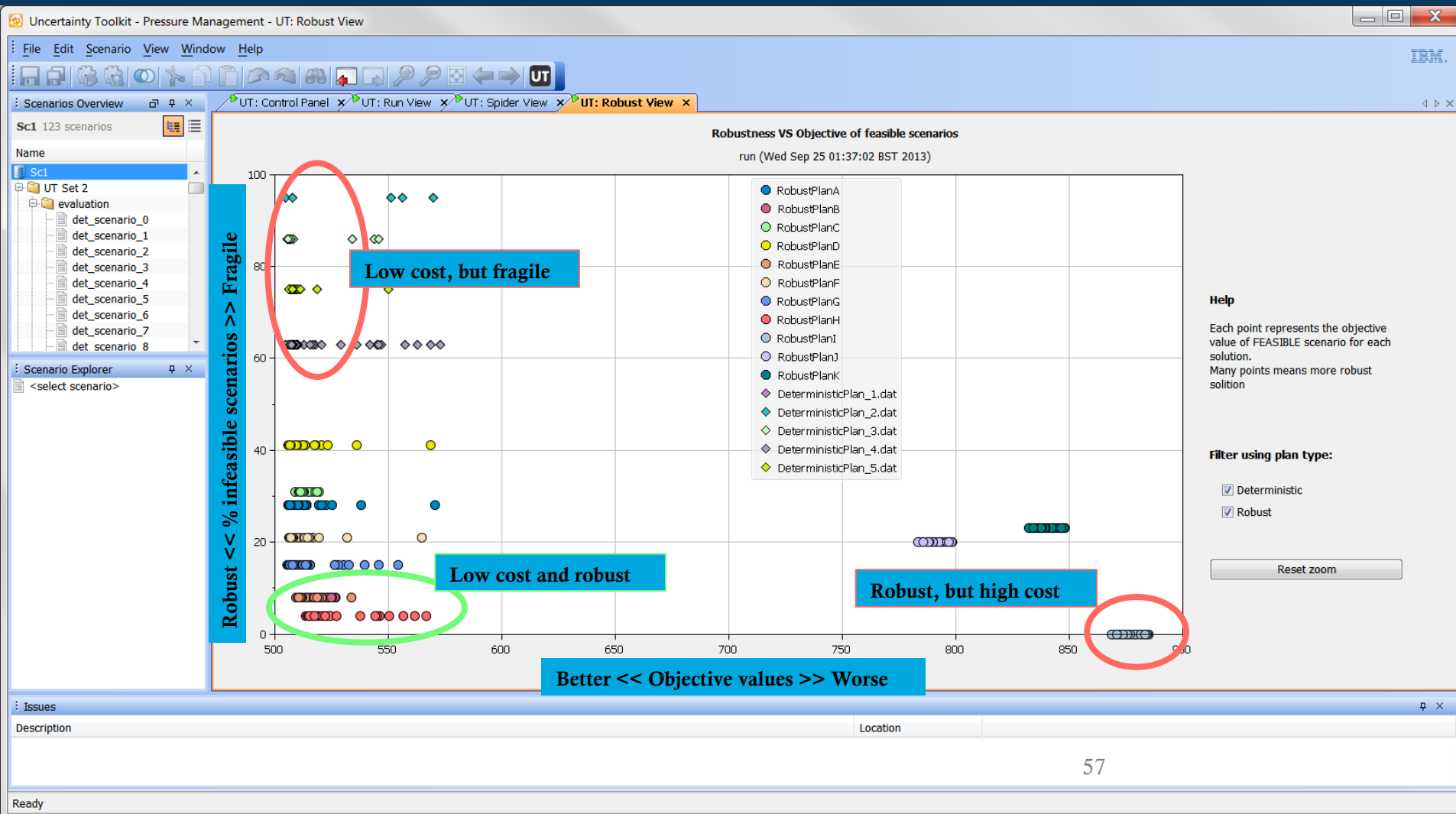
Benefits of Uncertainty Toolkit – pressure management use case



Pressure management use case:

Water network operational decisions 10 times more stable than current state, continue to perform well when data changes (i.e. “robust” plans)

Benefits of Uncertainty Toolkit – pressure management use case

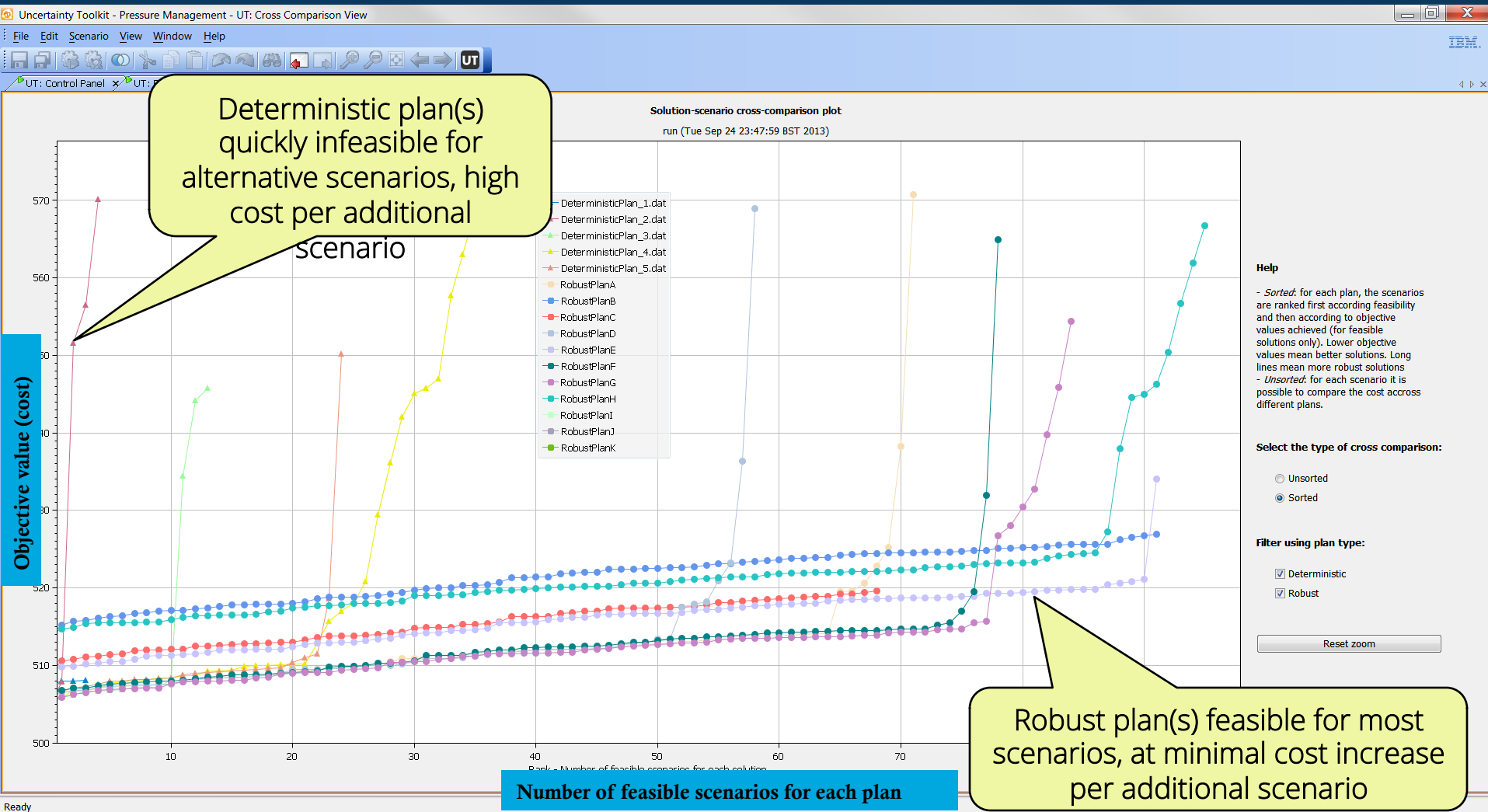


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Visualization of trade-off: robustness vs. cost



Benefits of Uncertainty Toolkit – pressure management use case



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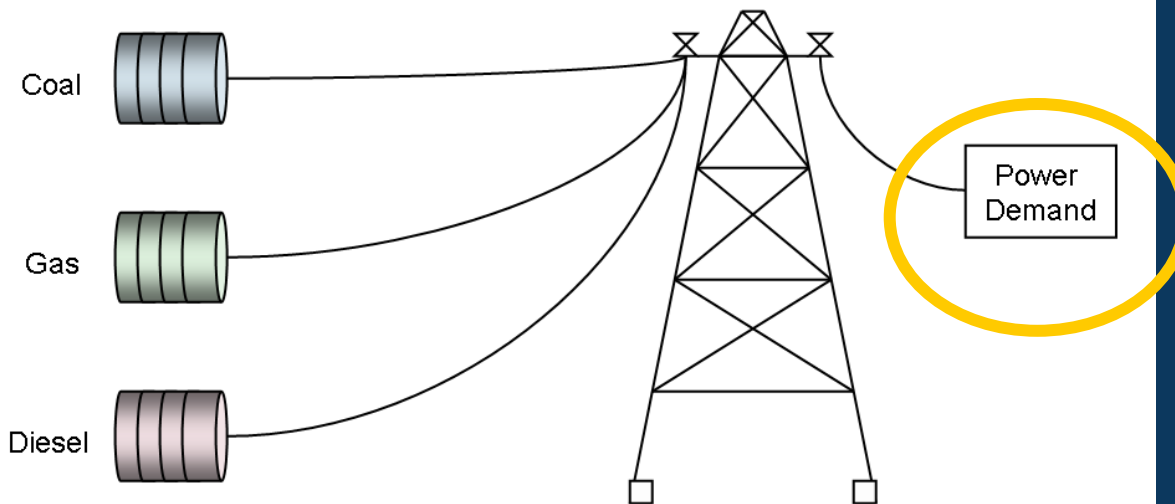
Effect on feasibility (robustness) by increasing cost



Example: Unit Commitment

The Unit Commitment Problem

3 types of power generators (units)



Business goal: Determine production schedule that minimizes startup cost + fuel cost + ecological cost (due to CO2 emissions), while satisfying demand

Lesson Title

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Uncertain
demand

Unit Commitment Problem

Given

- Power generation units with
 - Costs (start-up, fuel, CO2)
 - Operational properties (capacity, ramp)
- Demand over several periods

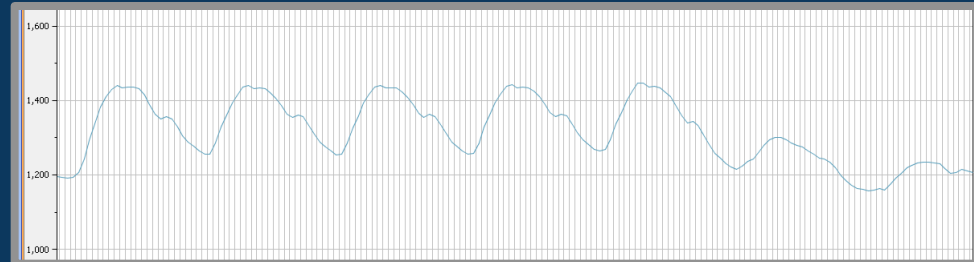
find generation plan

- Which units to use (unit commitment)
- How much to produce (dispatch)

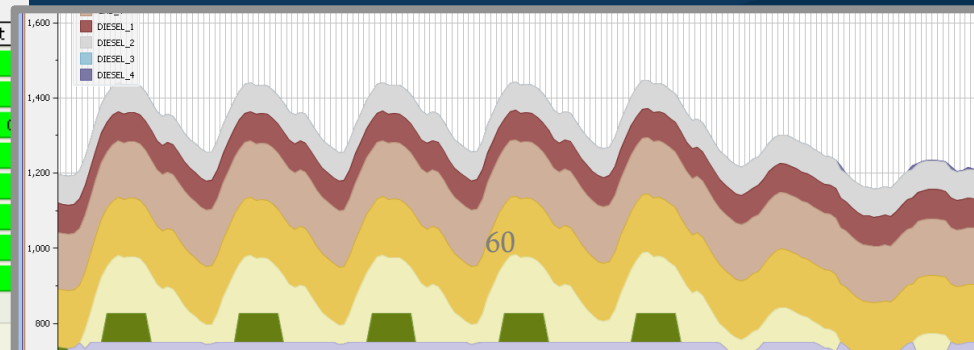
such that

- Demand is satisfied
- Operational constraints are satisfied
- Total cost is minimized

Type ↑	Name ↑	Linear Operations Cost	Fixed Start Up Cost	Linear Start Up Cost	CO2 Cost
Coal	COAL_1	\$22.536	\$5,000	\$208.607	\$30
	COAL_2	\$31.985	\$4,550	\$117.372	\$30
Diesel	DIESEL_1	\$40.222	\$560	\$54.417	\$15
	DIESEL_2	\$40.522	\$554	\$54.551	\$15
	DIESEL_3	\$116.331	\$300	\$79.638	\$15
	DIESEL_4	\$76.642	\$250	\$16.259	\$15
Gas	GAS_1	\$70.5	\$1,320	\$174.117	\$5
	GAS_2	\$69	\$1,291	\$172.754	\$5
	GAS_3	\$32.146	\$1,280	\$95.353	\$5
	GAS_4	\$54.84	\$1,105	\$144.517	\$5



Name	ID	Qty	...	March 2014	...	Wed 12	Thu 13	Fri 14	Sat
COA...	COAL_1	1							
COA...	COAL_2	1							
GAS_1	GAS_1	1	1	AS_1 is c			AS_1 is c		AS_1 is c
GAS_2	GAS_2	1							
GAS_3	GAS_3	1							
GAS_4	GAS_4	1							
DIES...	DIESEL_1	1							
DIES...	DIESEL_2	1							
DIES...	DIESEL_3	1							
DIES...	DIESEL_4	1							



Unit Commitment Problem – Stochastic Version

Problem: How to deal with uncertain loads?

Question:

- Is the dispatch plan still feasible under a slight perturbation of the load?

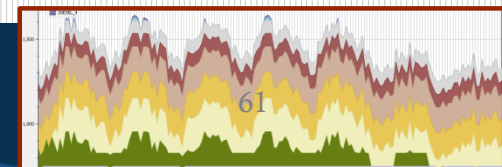
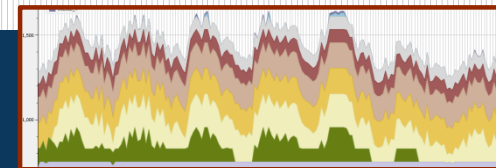
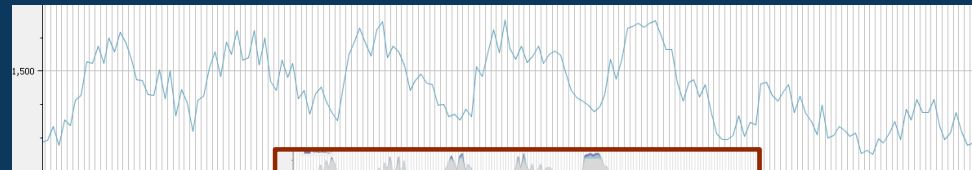
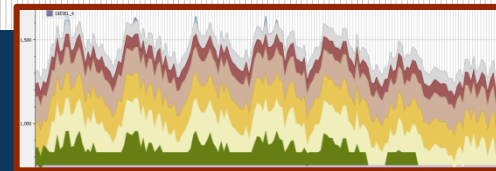
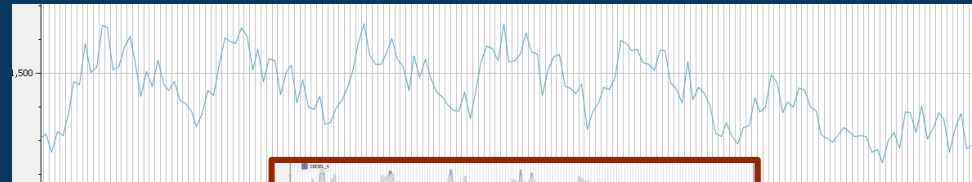
Stochastic Programming Approach

- Separate decisions into stages to be able to “react” to uncertainty

Decision Stages

- Stage 1: unit commitment
 - “Here-and-now” decisions
- Stage 2: dispatch
 - “Wait-and-see” decisions

Name	ID	Qty	... March 2014			
			... Wed 12	Thu 13	Fri 14	Sat 15
COA...	COAL_1	1				
COA...	COAL_2	1				
GAS_1	GAS_1	1	1	AS_1 is c	AS_1 is c	AS_1 is c
GAS_2	GAS_2	1				
GAS_3	GAS_3	1				
GAS_4	GAS_4	1				
DIES...	DIESEL_1	1				
DIES...	DIESEL_2	1				
DIES...	DIESEL_3	1				
DIES...	DIESEL_4	1				



Step 6a: Inspecting the results: Table View

UT: Control Panel X UT: Run View X **UT: Table View X**

Solution-scenario cross-comparison table
anne-stochastic-8scen-random0.1 (Fri Mar 14 00:55:35 CET 2014)

Select the KPI to show: Objective Value

Table cell width: 80

	scenario_0	scenario_1	scenario_2	scenario_3	scenario_4	scenario_5	scenario_6	scenario_7
Stochastic Plan	1.261418013E7	1.269088468E7	1.266713216E7	1.25511859E7	1.264070389E7	1.267165055E7	1.265699715E7	1.262302906E7
Deterministic Plan scenario_0	1.260033047E7							
Deterministic Plan scenario_1		1.267959751E7						
Deterministic Plan scenario_2			1.265528409E7					
Deterministic Plan scenario_3				1.253091733E7				
Deterministic Plan scenario_4					1.262720859E7			
Deterministic Plan scenario_5						1.265728358E7		
Deterministic Plan scenario_6							1.264521643E7	
Deterministic Plan scenario_7								1.261238517E7

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- Stochastic Plan is feasible for all scenarios

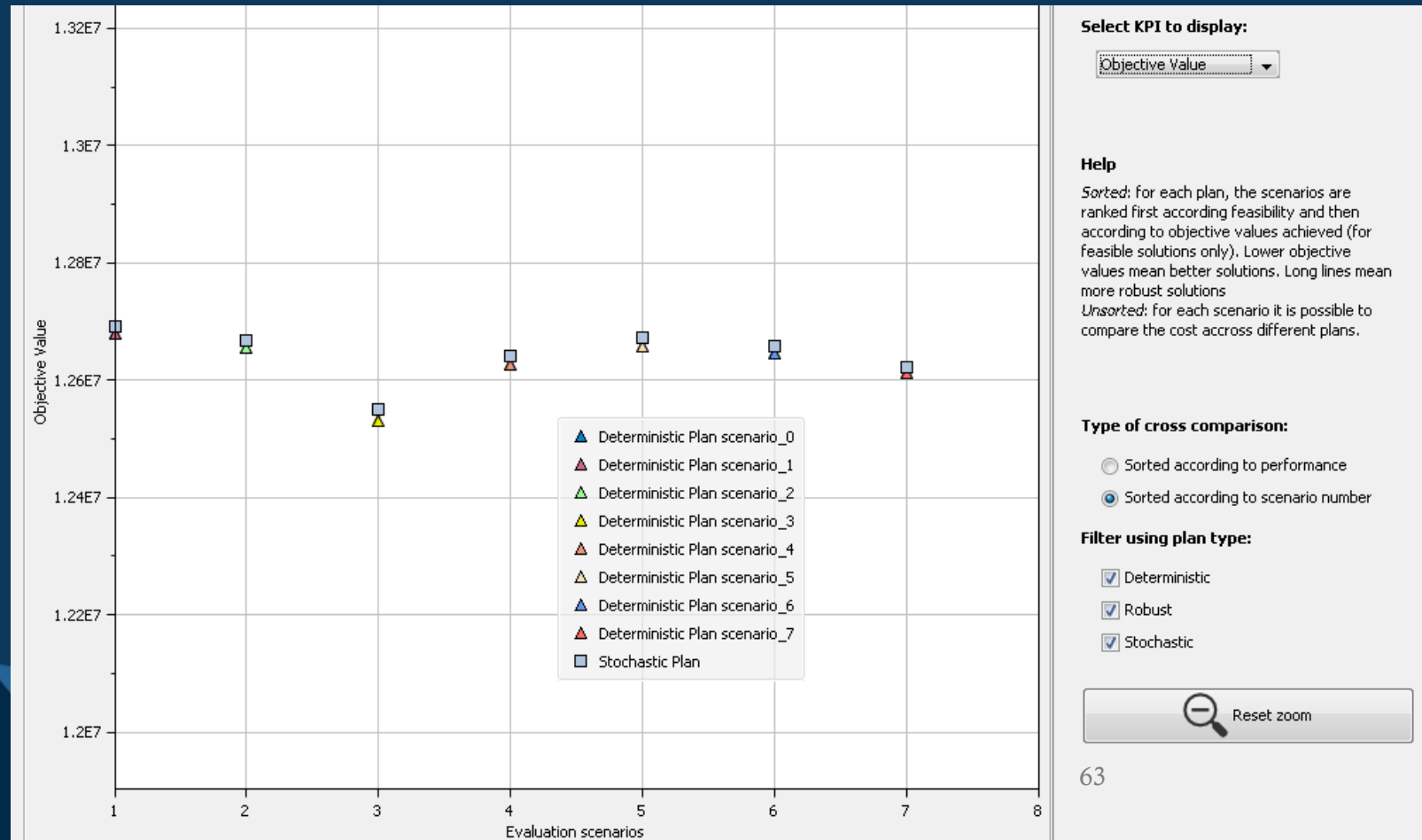


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Deterministic plans are only feasible for "their" scenario

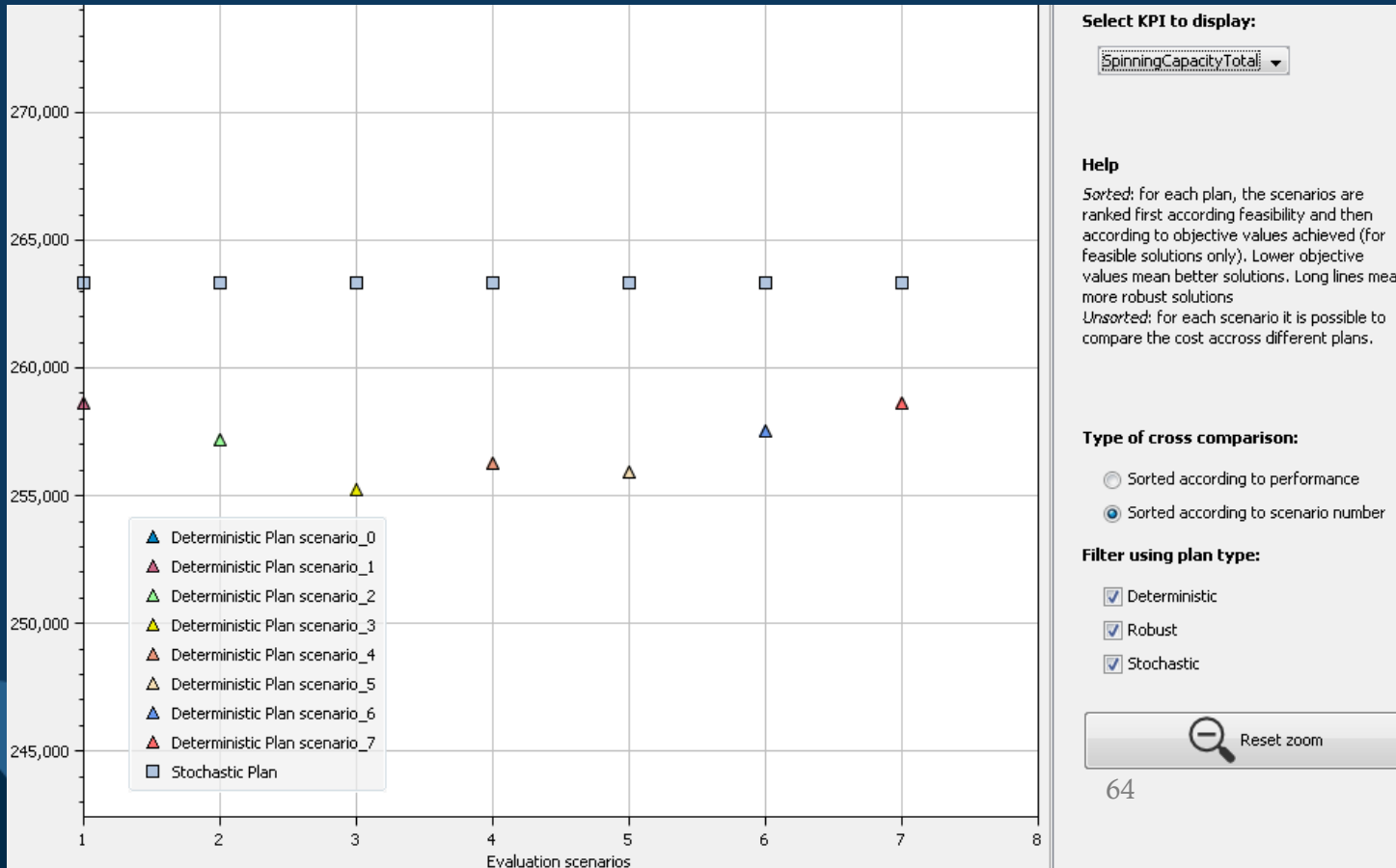


Step 6b: Solution-Scenario Cross-Comparison



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Step 6c: Cross-Comparison: Spinning Capacity



Summary

- Energy applications can benefit from Optimization
- Cplex Optimization Studio can speedup solving your problems and Deployment
- MIP is becoming standard for solving Energy Optimization Problems

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